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# A Comparison and Analysis of Internal and External Training Load Measures in Female Hockey Athletes

Natalie Konerth

2019



# **A Comparison and Analysis of Internal and External Training Load Measures in Female Hockey Athletes**

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## **Abstract**

The aims of this study were to investigate the various methods of measuring training load in female hockey athletes and to quantify the physical and physiological demands of female British university hockey. Monitoring athlete load and adjusting training dose accordingly has been shown to increase fitness, minimize injuries, and improve performance during competition in various sports; however, no research had previously been performed on effectively measuring training load in female hockey. An observational approach and repeated measures design were utilized, with ten outfield players from Durham University Hockey Club's Women's First Team monitored for the first half of the hockey season. Participants wore Minimax S4, 10 Hz GPS units (Catapult Sports, Melbourne, Australia) and Polar Team<sup>2</sup> heart rate monitors (Polar Electro, Kempele, Finland), and completed a submaximal lactate threshold treadmill test and maximal on-field fitness test at the beginning and end of the study. Following Stagno's training impulse (TRIMP) procedure, a new female TRIMP algorithm (fTRIMP) was developed. The training load measures recorded were differential session rating of perceived exertion, average percentage of maximum heart rate, Stagno's TRIMP, fTRIMP, individualized TRIMP, total distance, workrate ( $\text{m} \cdot \text{min}^{-1}$ ), distance in speed zones, and efficiency index. Female TRIMP was extremely strongly correlated with Stagno TRIMP ( $r=0.998$ ), with a consistent multiplicative factor of 1.3. Fitness test scores were most strongly correlated with average weekly distance covered at  $15.1\text{-}19.0 \text{ km} \cdot \text{hr}^{-1}$  ( $r=0.639$ ) and  $>19.0 \text{ km} \cdot \text{hr}^{-1}$  ( $r=0.842$ ) and efficiency index ( $r=0.785$ ). On the pitch during competition, participants averaged  $88.3 \pm 3.1\%$  of their maximum heart rate and covered  $5419 \pm 886 \text{ m}$ ,  $228 \pm 134 \text{ m}$  of which was at speeds  $>19.0 \text{ km} \cdot \text{hr}^{-1}$ . The demands of training were significantly lower than the demands of competition ( $p<0.01$ ) for all training load measures. The results of this study provide evidence in support of effective, individualized athlete monitoring in female hockey.



# **A Comparison and Analysis of Internal and External Training Load Measures in Female Hockey Athletes**

Natalie Konerth

A Thesis Submitted in Fulfillment of the Requirements  
for the Degree of

MASTERS OF SCIENCE BY RESEARCH

Department of Sport and Exercise Sciences

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2019





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## Chapter 1: Introduction

### 1.1 Background

Hockey is a field-based team sport in which teams of eleven athletes attempt to outscore opponents, using a curved stick to move the ball up the pitch and into the opponent's goal. With origins several thousand years before the first Olympic games, hockey is the world's oldest stick-and-ball game and an Olympic sport for both men and women (Lythe, 2008; Olympic.org, 2019). Similar to other field-based team sports, the demands of hockey are intermittent, with high speed running and sprinting interspersed with periods of stationary and active recovery (Gabbett, 2010; Polley *et al.*, 2015; McGuinness *et al.*, 2017). Because of this similarity, the majority of current practices for athlete monitoring in hockey have been based on other field-based team sports, such as football and rugby (Podgórski and Pawlak, 2011; Abbott, 2016). However, notwithstanding these parallels, hockey has several key characteristics that make it unique from other sports, demonstrating the need for hockey-specific research.

Unlike football and rugby, hockey has unlimited rolling substitutions, meaning that athletes on the pitch can freely substitute with athletes on the bench at almost any time (Abbott, 2016). As a result, hockey is played at a higher intensity than other field-based team sports, with athletes routinely averaging 85-89% of their maximum heart rate while on the pitch (Lythe, 2008; Sell and Ledesma, 2016; Vescovi, 2016; McGuinness *et al.*, 2017). In addition to the elevated intensity, rolling substitutions provide an increased challenge for data analysis, as time spent on the bench can confound time-dependent measures such as average speed (White and MacFarlane, 2013). Hockey also has no offsides or restraining lines, causing players' movement patterns to be stochastic in nature (McGuinness *et al.*, 2017). Finally, hockey athletes must assume a semi-crouched position while passing and dribbling, which has been shown to increase exertion and energy expenditure (Reilly and Seaton, 1990).

As a result of these differences, it is almost impossible to accurately apply research performed on other field-based team sports to hockey. Despite this fact, research on hockey has been extremely limited, with very few peer-reviewed studies published on hockey populations (Podgórski and Pawlak, 2011). Where there has been research on hockey, the majority of it has been performed on male hockey athletes. However, due to physical differences in male and female athletes, the strategies, skill sets and physical output of players differ greatly between the male and female game.

As personal tracking devices, such as heart rate monitors and global positioning system (GPS) trackers, have become more accurate and accessible, there has been a substantial increase in athlete monitoring during hockey (Podgórski and Pawlak, 2011). Monitoring training load and adjusting training dose accordingly has been shown to increase fitness, minimize injuries, and improve performance during competition in various sports, including football, handball, rugby, and hockey (Foster *et al.*, 2001; Liu *et al.*, 2013; Kevin and James, 2015; Mara *et al.*, 2015; Bourdon, 2017). However, there are several gaps in the literature for female hockey which this study aims to address.

### 1.2 Project Summary/Rationale

Training load is a measurement of an athlete's work during a session, expressed as a numerical score. Specifically, internal training load measures consider the physiological demand of exercise on the body, whereas external training load measures focus solely on physical output, regardless of the physiological response (Scanlan *et al.*, 2014). This study examined differential session rating of perceived exertion (sRPE), heart rate, and global positioning system (GPS) parameters measured in Durham University Hockey Club's (DUHC) Women's 1st Team.

This study considered if differential sRPE is a valid method of monitoring internal training load in hockey training and competition. Validity was determined by the strength of the correlations between sRPE and other training load measures. Although relatively strong correlations have been found ( $r=0.70-0.83$ ) between sRPE and heart rate and distance based training load measures in football, futsal, and youth hockey, differential sRPE had yet to be studied in hockey (Impellizzeri *et al.*, 2004; Scott *et al.*, 2013b; Wilke *et al.*, 2016; Scantlebury *et al.*, 2017b). From a practical perspective, sRPE is a beneficial measure as it may be used when athlete tracking devices are not available, as is the case in many hockey clubs.

Training impulse (TRIMP) is a heart-rate based measure of internal training load that summarizes an individual's heart rate over the course of a session into a single numerical score. The TRIMP algorithm has been modified specifically for teams of hockey athletes; however, only male athletes were studied (Stagno, Thatcher and Van Someren, 2007). A method of calculating individualized TRIMP (iTRIMP) based on an individual's blood lactate curve has also been developed, but it had not been tested in hockey athletes (Manzi *et al.*, 2009). This study developed a new algorithm for calculating TRIMP (fTRIMP) in female hockey athletes following the procedure described by Stagno, Thatcher and Van Someren

(2007), as well as determining iTRIMP scores for each athlete as outlined by Manzi et al. (2009).

The index of performance efficiency (effindex) is a ratio of external training load (total distance or average speed) to internal training load (TRIMP or average heart rate) that provides information on how efficiently the body is working during exercise (Torreno *et al.*, 2016). Effindex is a relatively new measure that has only been studied in football (Akubat, Barrett and Abt, 2014; Arrones *et al.*, 2014; Torreno *et al.*, 2016). However, effindex is well suited for use in hockey as the rolling substitutions naturally break the game into sections, and effindex can determine if a team's substitution patterns allow athletes to maintain similar levels of efficiency throughout a match. This study was the first to measure effindex in hockey and investigate how efficiency changed over the course of a competition.

Several studies have compared the intensity of hockey training and competition with mixed results (Gabbett, 2010; Polglaze *et al.*, 2015; White and Macfarlane, 2015a). This study used both internal and external training load measures, including TRIMP, average heart rate, sRPE, total distance, distance in speed zones, and workrate ( $\text{m} \cdot \text{min}^{-1}$ ) to compare the intensity of training drills and competition. As the most effective form of training has been shown to be that which best mirrors the movement patterns and intensity of competition (Abbott, 2016; Liu *et al.*, 2013), the objective was to determine if the demands of training drills were adequately preparing British university hockey athletes for competition.

Finally, this study compared the demands of hockey competition in this population to previously published results. Specifically, the measures compared include total distance, distance in speed zones, and average heart rate. Although studies have been performed on hockey at many levels, including the university level in the United States, this study was the first to measure these variables in British university hockey, which is unique in terms of season length, game frequency and training schedule (Vescovi and Frayne, 2015; Sell and Ledesma, 2016). A goal of this study was to determine if the results validate previous research or demonstrate that the demands of British university hockey differ from those of other hockey populations.

### 1.3 Research Questions

Overall, this study had two main aims: (1) investigating methods of measuring training load in female hockey athletes and (2) summarizing the demands of female British university hockey. The research questions associated with these aims are as follows.

### Measuring Training Load in Female Hockey Athletes:

- 1) Are there associations between different methods of measuring training load in female hockey athletes?
- 2) Which training load measure(s) best predicts fitness and fitness change?

### Physical and Physiological Demands of Female British University Hockey:

- 3) What are the physical and physiological demands of female British university hockey and how do these demands compare to other previously studied female hockey populations?
- 4) How do the demands of training compare to the demands of competition?

## 1.4 Significance

From a practical perspective, the results of this study have significant implications for female hockey training and athlete monitoring. Firstly, by determining which training load measure(s) best predicts fitness and fitness change, this study provides evidence on the most effective methods of monitoring training load in female hockey athletes. Coaches and sports scientists can use these results to ensure that athletes are being appropriately monitored, with training load measures linked to fitness outcomes, and are reaching target training load thresholds. As individualized monitoring has been shown to improve fitness, minimize injuries, and improve performance during competition, determining how to effectively monitor female hockey players can improve athletes' safety and performance (Foster *et al.*, 2001; Liu *et al.*, 2013; Kevin and James, 2015; Mara *et al.*, 2015; Bourdon, 2017). Furthermore, the associations between different training load measures provide information on the validity of easily computed training load measures, such as differential sRPE and average percentage of maximum heart rate, as well as on the need for both internal and external training load monitoring. As many hockey teams have limited resources, this information may simplify athlete monitoring protocols, making individualized monitoring more accessible to hockey clubs.

This study was the first to summarize the demands of British university hockey training and competition. As monitoring took place over several months, results included details on the demands of competition and training sessions, as well as on the demands of the hockey season as a whole. Comparisons with previously published results provide information on how the demands of British university hockey compare with other national and international level competition. Finally, in order for training to be most effective, it must

be performed at the same intensity as competition (Liu *et al.*, 2013; Abbott, 2016). By comparing the demands of training and matches, the results of this study include evidence on whether small-sided games used in a training environment adequately prepare athletes for competition. Thus, this study provides information to coaches on whether commonly used small-sided games are an adequate training drill to prepare athletes for the demands and intensity of match play.



## **Chapter 2: Literature Review**

### 2.1 Introduction

This literature review will critically examine the current empirical research on and history of internal and external training load measurement. Although the emphasis will be on hockey, other sports will be discussed, particularly when considering training load measures that have not yet been studied in hockey athletes. This review will begin with a general introduction to the sport of hockey and the concept of training load and then will go into detail on specific training load measures. First to be examined is session rating of perceived exertion (sRPE), which has been extensively researched in other sports, but has yet to be investigated in adult hockey, despite its potential as an easily calculated metric. The next measure is training impulse (TRIMP), which involves using one of several published algorithms to summarize heart rate data from an entire session into a single numerical score. The TRIMP algorithms have evolved over time from general equations to more specific hockey-based formulas and even individualized calculations; however, none of these algorithms have been studied in female hockey athletes. In addition to the internal measures of sRPE and TRIMP, this literature review will examine external training load measures, such as distance, workrate, and distance in speed zones, derived from GPS data. Although these measures have been extensively researched in hockey, there is little consensus across various hockey populations, and no study has examined British university hockey. Finally, this literature review will conclude by investigating what can be learned by examining internal and external training load measures simultaneously. Specifically, the potential benefits of measuring efficiency index (effindex), the ratio of external and internal training load, will be considered. In summary, the goal of this literature review is to provide a thorough outline of the existing literature surrounding training load in female hockey athletes and to identify the gaps in the literature that this study intends to address.

#### 2.1.1 Demands of Hockey

Hockey is a stick-and-ball based, goal-scoring, field sport. It originated several thousand years before the first ancient Olympics and evolved over time, with the first official international hockey matches taking place in the late 19<sup>th</sup> century (Lythe, 2008). During matches, there are 11 athletes on the pitch, typically 10 field players and a goalkeeper, and teams work to win and maintain possession, move the ball up the pitch, and outscore their opponents. Elite hockey is played on a synthetic, water-based turf, sized at 100 by 60 yards (91.4 by 55.0 m) and is an Olympic sport for both men and women (Abbott, 2016). Although

there are many different playing structures, outfield players are typically grouped into three main positions, defense, midfield, and forwards (also known as strikers). Games of hockey traditionally consist of two 35-minute halves with a continuous game clock, only stopped for injuries and egregious fouls (Abbott, 2016). However, at the international level, hockey is now played in 15-minute quarters with pauses in the game clock for goals and certain penalties. As a result, there has been a decrease in the amount of low-intensity movements, such as walking, that athletes perform during the game, but no recorded difference in average heart rate (Abbott, 2016; McGuinness *et al.*, 2017). This change in game timing is not unprecedented, as the game of hockey is continually developing, with new rules being introduced over time, such as unlimited substitutions (1992), the removal of offsides (1998), and the self-pass (2009) (Macutkiewicz and Sunderland, 2011).

Like other field-based team sports, including football and lacrosse, the physical demands of hockey are intermittent in nature, as high-speed running is intermixed with accelerations, decelerations, and periods of stationary and active recovery (Gabbett, 2010; Polley *et al.*, 2015; McGuinness *et al.*, 2017). The intensity of hockey competition is high, with male athletes covering upwards of 7.3 km on average (Liu *et al.*, 2013), and athletes' average heart rate on pitch ranging from 85-89% of their maximum heart rate (Lythe, 2008; Sell and Ledesma, 2016; Vescovi, 2016; McGuinness *et al.*, 2017). Hockey athletes must also adopt a semi-crouched position when passing, receiving, and dribbling, which has been shown to increase heart rate, energy expenditure, and perceived exertion when compared to normal running (Reilly and Seaton, 1990). With possession of the ball frequently changing and there being no offsides or restraining lines, the movement patterns of hockey players are stochastic, or random, in nature (McGuinness *et al.*, 2017). As a result of the random movement, without appropriate tracking devices or video technology, hockey can be a challenging sport to analyze and quantify. In addition, a key difference between hockey and sports such as rugby and football is the rule allowing for unlimited, rolling substitutions (Abbott, 2016). Except during penalty corners (a set play that occurs when there is a foul in the scoring area), players may substitute at any time. Depending on the tournament or league, typically five to seven players are available and recovering on the bench, allowing teams to maintain a high-intensity on the field for the duration of the match (Abbott, 2016).

In terms of research, there are a very limited number of peer-reviewed studies focused on hockey, and even fewer on female hockey. A systematic review of scientific journal articles on hockey between 1960 and 2010 found only 208 studies (Podgórski and Pawlak, 2011). However, a search for field hockey studies published after 2010 yielded 101 results,

suggesting that although research into hockey is still very limited in comparison to other sports, there has been a recent upswing in hockey research. As a comparison, the academic database EBSCOhost returned 7,459 results when searching for ‘field hockey’ compared to 1,024,038 for football, 570,309 for basketball, and 22,700 for lacrosse (Podgórski and Pawlak, 2011). The majority of studies were published by authors in the United States (21.15%), the United Kingdom (20.67%), and Australia (13.94%) (Podgórski and Pawlak, 2011). Specifically considering articles on monitoring load in athletes, there have been a range of studies performed on both international and national level athletes. Although published data on international teams are often limited as teams prefer to keep their findings from potential competition, there are published studies on the women’s national teams from the United States (Abbott, 2016) and Canada (Vescovi, 2014; 2016) and the men’s national teams from Australia (Spencer *et al.*, 2004; Polglaze *et al.*, 2015; Jennings *et al.*, 2012a; 2012b), Scotland (White and MacFarlane, 2013; 2015a), and New Zealand (Lythe, 2008). Additionally, in terms of national level competition, there have been studies on the Chinese Men’s National Games (Liu *et al.*, 2013), the Australian Hockey League, both male (Jennings *et al.*, 2012b) and female (Gabbett, 2010), US Women’s Division I University Hockey (Sell and Ledesma, 2016; Vescovi and Frayne, 2015), the English Women’s Premier League (Vinson, Gerrett and James, 2017; Sunderland and Edwards, 2017), and the Scottish Women’s National League (White and Macfarlane, 2015b); however, there have yet to be any studies performed on British university hockey. Unlike athletes in other national-level leagues, elite British university athletes compete in two games per week instead of one. Additionally, the season structure and schedule of British university hockey differ greatly from university hockey in the US, as the season is much longer, running from October-April rather than September-November, and training sessions are less frequent, with US athletes typically training 4 times per week in season compared to 2 times per week for British athletes (Sell and Ledesma, 2016). Therefore, British university hockey represents a unique hockey population that has yet to be studied.

### 2.1.2 Measuring Training Load

As the object of hockey is to win games by outscoring opponents, a main goal of coaches is to prepare and peak athletes for competition (Banister, 1991). Thus, coaches seek to design training and preparation to maximize the potential of their athletes on match-day. However, determining the necessary training dose and measuring physical outputs is incredibly difficult, requiring professional expertise and intelligent planning, as without

tracking equipment, it is impossible to know the exact physiological and physical work performed (Bompa, 1999). As a result, many coaches often erroneously rely on intuition when making training decisions (Bompa, 1999). The concept of training load resolves this issue by measuring and quantifying the work of athletes, in both training and competition environments. Training load was first tracked in endurance sports through logs of training volume (kilometers per week) (Foster *et al.*, 2001). However, monitoring total distance provides no information on the intensity at which the training was performed. Additionally, unlike individual sports, such as running, swimming, and cycling, it is not feasible to plan and record the volume of training in team sports without sophisticated tracking devices. Even as tracking devices, such as heart rate and GPS monitors, have become available, the intermittent nature of field sports makes accurately quantifying the demands of training sessions and competitions far more challenging (Stagno, Thatcher and Van Someren, 2007). As a result, many different techniques have been developed to monitor training load in team-sport athletes.

Measures of training load can be grouped into two categories, internal and external. Internal training load is the physiological stress imposed on the body during training or competition (Scanlan *et al.*, 2014). Thus, internal training load measures include rating of perceived exertion (RPE), heart rate (often measured as TRIMP), oxygen consumption, and lactate accumulation (Scanlan *et al.*, 2014; Bourdon, 2017; Macleod *et al.*, 2009). Although varied, these measures all examine the physiological demands of exercise on the body. On the other hand, external training load is an objective measure that focuses solely on physical output, regardless of the internal physiological response (Bourdon, 2017). External training load is movement-based and, as such, is often measured through time-motion analysis, GPS parameters, power output, or accelerations (Bourdon, 2017; Scott *et al.*, 2013a). Although different constructs, both internal and external measures have been successfully used to monitor training load across a large range of sports (Scott *et al.*, 2013a).

Measuring training load has been shown to be incredibly beneficial, despite the additional effort, knowledge, and hardware required (Bourdon, 2017). There have been numerous studies on the benefit of training programs that combine periods of lower and higher intensity work through periodization (Morton, Fitz-Clarke and Banister, 1990; Busso *et al.*, 1997; Mujika, 1998; Bompa, 1999; Foster *et al.*, 2001; Kevin and James, 2015; Mara *et al.*, 2015). However, without effective measures of monitoring training load, it can be impossible to determine if a training prescription is being met (White and Macfarlane, 2015a). Furthermore, it has been shown that for field-based team sports, including football,

handball, basketball, rugby, and hockey, the most effective type of training is that which best mirrors the intensity of competition (Gabbett, 2010; Liu *et al.*, 2013). For this reason, it is important to determine the demands of competition and measure load during training to ensure that training intensity is appropriately planned and executed. Finally, monitoring training load is crucial to minimizing both overtraining and undertraining (Bompa, 1999; Stagno, Thatcher and Van Someren, 2007; Cummins *et al.*, 2013). Individuals respond to training stimuli differently, and it has been repeatedly shown that there are different physical demands across hockey positions – forwards, midfield, and defense – with the average distance covered during a game varying by as much as 2.3 km between positions (Gabbett, 2010; Sunderland and Edwards, 2017; Vescovi, 2016; McGuinness *et al.*, 2017; Boran, 2012). Therefore, monitoring training load allows coaches to individualize training programs to ensure that each athlete receives the appropriate training dose. Both too high and too low a training load have been shown to increase the risk of injury, so monitoring load can reduce injuries (Bourdon, 2017). In conclusion, when implemented correctly, monitoring training load can help to improve performance, avoid over and under training, and decrease injuries. In the subsequent sections, RPE, TRIMP and GPS tracking will be considered as methods of measuring training load in hockey.

## 2.2 Rating of Perceived Exertion (RPE)

Rating of perceived exertion (RPE) is a subjective, perceptual method of monitoring internal training load. Specifically, RPE is the athlete's perceived level of exertion at any specific time, or range of times, during exercise (Martin, 2012). Collecting RPEs involves asking athletes to report how difficult or exerting they found an activity or session, as increases in physiological fatigue have been shown to be associated with increased exertion levels (Davis and Walsh, 2010).

There are several different scales and methods that can be used to measure RPE. Traditionally, RPE values were determined using the 15-point Borg Rating of Perceived Exertion Scale (Martin, 2012). This scale, which was first introduced in the 1960s, goes from six to twenty, with higher numbers indicating increased exertion levels (Chen, Fan and Moe, 2002). Borg reported a strong correlation ( $r=0.83$ ) between perceived exertion and heart rate on a cycle ergometer, and, in the following decades, Borg's scale became very popular (Borg, 1962; Chen, Fan and Moe, 2002). However, as more studies were performed, the validity of Borg's RPE scale came into question (Kolkhorst, Mittelstadt and Dolgener, 1996; Travlos and Marisi, 1996; Zeni, Hoffman and Clifford, 1996; Chen, Fan and Moe, 2002; Faulkner

and Eston, 2007). Specifically, a meta-analysis of 437 studies found the weighted mean validity coefficients for the Borg RPE scale to be only  $r=0.62$  for heart rate,  $r=0.57$  for blood lactate, and  $r=0.64$  for maximal oxygen intake (Chen, Fan and Moe, 2002). These weaker correlations suggest that Borg's RPE scale is not nearly as strongly related to the body's physiological response to exercise as was initially reported, and, therefore, is not a very accurate measure of internal training load (Chen, Fan and Moe, 2002).

### 2.2.1 Session RPE

In contrast to Borg's RPE rating, session RPE takes into consideration the duration of exercise sessions. Initially, RPE was collected by asking, using precise instructions, how exerting an athlete found an activity at a given moment (Foster *et al.*, 2001). Although useful in assessing the level of exertion at a fixed point in time, this provides little information on a training session as a whole, particularly during intermittent exercise. In order to resolve this problem, Foster *et al.* created a session rating of perceived exertion (sRPE) method in which athletes are asked for a "global rating" of training session intensity, using a 0-10 scale with set descriptors (CR10 scale) (Foster *et al.*, 2001). To account for variation in the length of training sessions, the reported value is multiplied by total session time (in minutes) to determine sRPE .

A variety of studies have investigated the validity of sRPE as a method of monitoring training load in intermittent field-based team sports. A study of 19 football players across 27 training sessions found a moderate correlation ( $r=0.70$ ) between mean team sRPE and TRIMP (Impellizzeri *et al.*, 2004). Similarly, a study of 21 male Australian football players monitored across 38 training sessions compared sRPE to measures of both internal and external training load (Scott *et al.*, 2013b). The results showed relatively strong correlations between sRPE and TRIMP ( $r=0.83$ ) and between sRPE and total distance ( $r=0.78$ ) (Scott *et al.*, 2013b). Furthermore, a 2016 study compared sRPE with TRIMP across 37 training session in 12 elite futsal athletes and found a moderate correlation ( $r=0.70$ ) (Wilke *et al.*, 2016). However, the strength of the correlation varied significantly between individuals ( $r=0.11 - 0.70$ ), (Wilke *et al.*, 2016). As the study took place during technical-tactical training sessions, the researchers hypothesized that this range of correlations was due to differing mental, not physiological, strain experienced by the individuals (Wilke *et al.*, 2016). However, regardless of the cause, these findings suggest that some individuals' perceptions of exertion are more accurate reflections of the body's physiological response to exercise than others, and, thus, extreme caution should be taken when considering an individuals'

sRPE data in isolation. Overall, these studies suggest that there is a moderate to strong correlation between team average sRPE and other measures of training load. Thus, sRPE may be a useful measure of internal training load, particularly when other more sophisticated measures are not available. However, the correlation coefficients ranging from  $r=0.70$  to  $r=0.83$  indicate that there are other factors, such as emotional or psychological strain, affecting sRPE values, and one should be cautious when drawing conclusions from sRPE.

### 2.2.2 Differential RPE

An expansion of sRPE, called differential rating of perceived exertion (dRPE), has been developed to provide additional information and explain some of the factors influencing sRPE (McLaren *et al.*, 2017). Differential RPE involves athletes reporting separate RPE scores for various elements of exertion, such as breathlessness, lower body muscular exertion, and upper body muscular exertion (Arcos *et al.*, 2014). As respiratory and muscular fatigue both contribute to overall feelings of exertion, the concept behind dRPE is to isolate these different types of effort to provide more detailed and specific information on the various demands of a training session (Weston *et al.*, 2015; McLaren *et al.*, 2017). In a study of professional rugby-union players, dRPE scores for breathlessness, leg muscle exertion, upper body exertion, and cognitive/technical demands combined to explain 84% of the variance in overall sRPE during small-sided training games and 91% during repeated high-intensity effort conditioning (McLaren *et al.*, 2017). Thus, dRPE scores give a more detailed representation of internal load by explaining much of the variability in sRPE which is impossible to determine when considering sRPE alone (McLaren *et al.*, 2017).

Several studies have investigated the relationship between dRPE and various other methods of measuring training load and fitness in male populations. (Arcos *et al.*, 2014; 2015; Gil-Rey, Lezaun and Los Arcos, 2015; Weston *et al.*, 2015). Firstly, a study of dRPE in professional football players found that TRIMP was strongly correlated with both muscular ( $r=0.84$ ) and respiratory ( $r=0.87$ ) dRPE, suggesting that dRPE is a valid measure of internal training load (Arcos *et al.*, 2014). However, the relationship between dRPE and external training load measures may be much weaker, with a study on Australian football players finding extremely weak correlations between high speed running distance ( $>14.4 \text{ km} \cdot \text{h}^{-1}$ ) and dRPE for leg exertion ( $r=0.31$ ) and breathlessness ( $r=0.17$ ) (Weston *et al.*, 2015). However, this study removed the time component of sRPE, considering a 1-10 score rather than multiplying that score by session time, which likely contributed to the lower correlations (Weston *et al.*, 2015). Additionally, studies assessing the relationship between dRPE and

fitness changes have found mixed results. Specifically, a nine-week study of 19 male professional football players found the sum of an individual's dRPE scores to be weakly negatively correlated ( $r=-0.57$ ) with fitness improvements, as measured by lactate concentration at  $13 \text{ km}\cdot\text{h}^{-1}$  during fitness tests performed at the start and end of the study (Arcos *et al.*, 2015). This suggests that athletes may have reached a point of overtraining and fatigue, which would explain why increased exertion levels during training were associated with decreased fitness (Bompa, 1999). However, another study, also on male professional football players over a nine-week period, found both respiratory and muscular dRPE to be positively correlated with fitness improvement ( $r=0.71$  and  $r=0.69$ , respectively), as measured by time to exhaustion in a continuous, maximal multistage fitness test (Gil-Rey, Lezaun and Los Arcos, 2015). Thus, in this case, higher cumulative dRPE ratings were associated with fitness improvements, perhaps suggesting that the participants in the study were not overtrained, so a training effect took place with an elevated training stimulus resulting in fitness improvements (Bompa, 1999). Overall, although it is clear that measuring dRPE can provide additional information compared to sRPE, these studies indicate the need for further research on the relationship between dRPE and fitness changes, particularly in female populations.

### 2.2.3 Advantages and Disadvantages of RPE

When considering collecting RPE scores, whether sRPE or dRPE, there are several benefits and limitations that should be noted. Firstly, the notion of RPE is based on the idea that athletes can monitor their own exertion levels during exercise and accurately report them at the end of a session or competition (Halsen, 2014). Essentially, the theory is that the simplest way to gain information on how physiologically taxing a session was for a group of athletes is to ask them. Furthermore, by using a numerical scale, researchers and sports scientists can obtain quantitative information that can be used in analysis, rather than qualitative responses which can be difficult to quantify. Unlike methods for monitoring heart rate and distance travelled, which require sophisticated hardware and software, collecting RPEs requires no additional expense, set-up, or equipment. Because of this, RPEs can be easily collected from large groups of athletes and are particularly useful for teams with limited resources. Furthermore, even for teams that do use other monitoring methods, particularly of external training load, collecting sRPE data can help coaches and trainers understand individual athletes' responses to a training stimulus (Gallo *et al.*, 2014). Since athletes will have varied physiological responses to identical external stimuli, and some



athletes will require longer for recovery, the additional information provided by RPE scores can be used to personalize training prescriptions to help prevent undertraining and overtraining (Impellizzeri, Rampinini and Marcora, 2005; Gallo *et al.*, 2014). Additionally, many outside factors, such as sleep, anxiety, hydration, and ambient temperature, can impact the body's response to an external training stimulus, thereby affecting RPE (Martin, 2012). Thus, monitoring RPE can provide insight on outside factors affecting performance.

Although there are clearly many advantages of collecting RPE, there are also several limitations that should be considered. Firstly, it can be easy to think that monitoring RPE does not require technical expertise, especially when compared to heart rate and GPS measures. However, outside factors affect RPE, so careful and experienced interpretation of these values is critical (Gallo *et al.*, 2014). For example, an athlete's psychological state, including factors such as mood and mental fatigue, have been shown to impact sRPE scores (Marcora, Staiano and Manning, 2009; Blanchfield *et al.*, 2014; Gallo *et al.*, 2014). For example, a study of 16 individuals found that subjects reported significantly higher RPE scores ( $p=0.007$ ) during physical activity after completing a 90-minute cognitively exhausting computer test compared with a non-stimulating control activity, despite there being no significant difference in heart rate or blood lactate prior to exhaustion (Marcora, Staiano and Manning, 2009). Furthermore, self-talk training and self-efficacy scores prior to exercise have also been shown to significantly affect RPE scores ( $p<0.05$ ,  $p<0.001$ ) (Rudolph and McAuley, 1996; Blanchfield *et al.*, 2014). In competition settings, opponent and outcome can also impact RPE (Gabbett, 2013). Specifically, a study of 22 elite male rugby players found that RPEs scores were highest in games against top-ranked teams as well as games won by small margins or lost by large margins (Gabbett, 2013). Thus, the perception of the opponent as well as the final score, which influences psychological state after a game, will impact the reporting of perceived exertion. Finally, it is important to consider that athletes may alter their RPE scores to attempt to elicit a change in future training sessions, or because they wish for a coach to think that they were exerting maximal effort, particularly in competition settings. Therefore, it is critical for coaches to be aware of these influencing factors when making decisions based on RPE scores.

Focusing specifically on hockey, there has only been one study to date assessing the validity of sRPE in hockey athletes. Although this study claimed to have demonstrated that sRPE was a valid measure of monitoring internal training load in hockey athletes, the correlation between sRPE and TRIMP was only moderate ( $r=0.6$ ) (Scantlebury *et al.*, 2017a). Furthermore, the population was small (nine participants), was made up of youth athletes, and

only training sessions were considered, rather than both training and competition (Scantlebury *et al.*, 2017a). Thus, there is still a significant gap in the literature on the validity and reliability of sRPE and dRPE in hockey populations. Many hockey clubs do not have access to monitoring equipment such as GPS and heart rate monitors; therefore, if sRPE and dRPE are found to be valid measures, they could be used to monitor training load in hockey athletes on whom monitoring would otherwise not be possible.

### 2.3 Training Impulse (TRIMP)

Like RPE, training impulse (TRIMP) is a method of measuring internal training load. However, instead of being a subjective measure based on perceptions of exertion, it is objective and derived from an individual's heart rate. As with all internal training load measures, TRIMP is based solely on the physiological response to an exercise session with no regard to the actual physical output produced. TRIMP is designed to express and summarize the total work of an individual across an entire training session in a single numerical value in arbitrary units (Needham, 2011). Originally intended to be “a unit measure of training that can quantify physical effort,” it incorporates both duration and training intensity (determined by heart rate) as well as a weighting factor based on the body's physiological response to exercise (Banister, 1991). Over time a variety of different methods for calculating TRIMP have been developed; however, regardless of formula, the goal is to use heart rate data to create a numerical score for the physiological load of an exercise session.

Heart rate is a well-established method of monitoring exercise intensity that has been in use since the late 1960s (Conway, 2016). Exercising heart rate has been shown to be a good candidate for monitoring internal training load as it is relatively consistent when repeating the same training regimen, and heart rate increases as intensity elevates (Banister, 1991). Additionally, technological improvements and the increased availability of heart rate monitors have led to a rise in team heart rate monitoring, both in training and competition (Conway, 2016). However, just considering average heart rate or maximum heart rate provides little information on a training session as a whole, as duration is ignored and the intermittent nature of activities can be obscured. Therefore, TRIMP has been established as a method of synthesizing and summarizing heart rate data across an entire training session.

### 2.3.1 History of TRIMP

The concept of TRIMP was first introduced by Banister in 1991 to quantify training activities where heart rate reaches steady-state (levels out and remains consistent). The equation for calculating Banister's TRIMP is as follows.

*Equation 2.1: Banister's TRIMP Equation (Banister, 1991)*

$$TRIMP = \text{training duration (minutes)} \times \frac{HR_{ex} - HR_{rest}}{HR_{max} - HR_{rest}} \times y$$

where

*Equation 2.2: Banister's TRIMP Sex Weightings (Banister, 1991)*

$$y = 0.64e^{1.92\left(\frac{HR_{ex}-HR_{rest}}{HR_{max}-HR_{rest}}\right)} \quad (\text{male})$$

$$y = 0.86e^{1.67\left(\frac{HR_{ex}-HR_{rest}}{HR_{max}-HR_{rest}}\right)} \quad (\text{female}).$$

$HR_{ex}$  is average heart rate during exercise,  $HR_{rest}$  is resting heart rate,  $HR_{max}$  is maximum heart rate, and  $e$  is the Naperian logarithm, 2.712 (Banister, 1991). The weighting factor,  $y$ , is incorporated to prevent giving disproportionate weight to low-intensity activities performed for a long duration and is based on classic curves modeling the blood lactate response to exercise in trained individuals (Banister, 1991). As an example, consider a female with a resting heart rate of 50 bpm and a maximum heart rate of 200 bpm who exercised for 60 minutes at an average heart rate of 150. Using Banister's (1991) algorithm, her TRIMP score is calculated as follows.

*Equation 2.3: Banister's TRIMP Example*

$$TRIMP = \text{training duration (minutes)} \times \frac{HR_{ex} - HR_{rest}}{HR_{max} - HR_{rest}} \times 0.86e^{1.67\left(\frac{HR_{ex}-HR_{rest}}{HR_{max}-HR_{rest}}\right)}$$

$$TRIMP = 60 \times \frac{150 - 50}{200 - 50} \times 0.86e^{1.67\left(\frac{150-50}{200-50}\right)}$$

$$TRIMP = 60 \times \frac{2}{3} \times 2.618$$

$$TRIMP = 104.73 \quad (\text{arbitrary units})$$

Although useful in measuring training load in steady-state activities, the use of mean heart rate in this equation fails to properly reflect the demands of intermittent team sports (Stagno, Thatcher and Van Someren, 2007). Specifically, when averaging heart rate data from an entire match, short bouts of very high intensity will have little influence on the mean due to their duration, despite having significant physiological effect. In order to overcome this limitation, Edwards (1993) proposed a summated heart rate zone approach to calculating TRIMP. This method involves grouping heart rate measures into five zones: zone 1= 50-60%

HR<sub>max</sub>, zone 2 = 60-70% HR<sub>max</sub>, zone 3= 70-80% HR<sub>max</sub>, zone 4= 80-90% HR<sub>max</sub>, and zone 5= 90-100% HR<sub>max</sub> (William *et al.*, 2015). TRIMP is then calculated as follows (William *et al.*, 2015).

*Equation 2.4: Edward's TRIMP Equation (Edwards, 1993)*

$$TRIMP = 1 \times (\text{time in zone 1}) + 2 \times (\text{time in zone 2}) + 3 \times (\text{time in zone 3}) \\ + 4 \times (\text{time in zone 4}) + 5 \times (\text{time in zone 5})$$

The use of summated zones better models the intermittent nature of team sports, as times spent at differing intensities are incorporated and weighted in the overall TRIMP score (Stagno, Thatcher and Van Someren, 2007). However, this model is still limited by the fact that the zones and weightings are arbitrary, rather than based on the body's physiological response to exercise (Stagno, Thatcher and Van Someren, 2007). In addition, it has been shown that metabolic stress is not the same across individuals exercising at the same percentage of maximum heart rate, as anaerobic thresholds vary between individuals (Stagno, Thatcher and Van Someren, 2007). Furthermore, individuals have unique blood lactate curves, so they will have varied accumulations of blood lactate at the same percentage of maximum heart rate. As a result, more individualized methods of measuring TRIMP have been developed.

### 2.3.2 Current TRIMP Models

Although Banister's and Edward's TRIMP models are often still used in research (Scott *et al.*, 2013b; Luke, Brendan and Mark, 2015; Marques *et al.*, 2017; Silva *et al.*, 2017; Slimani *et al.*, 2017; Turner *et al.*, 2017), new methods have been developed to more accurately model TRIMP based on the body's physiological response to exercise. The first method, which is particularly of note as it was developed in hockey athletes, is a modified TRIMP using summated heart rate zones. To develop the algorithm, Stagno, Thatcher, and Van Someren (2007) studied 8 male hockey players from the English Premier Division over the course of a hockey season. Subjects performed a submaximal treadmill test, which consisted of four 4-minute intervals starting at a speed of 10 km·hr<sup>-1</sup> and increasing by 2 km·hr<sup>-1</sup> each stage, with a 1-minute rest between stages. During the rest time, capillary blood samples were taken and analyzed for lactate, and these measurements were used to extrapolate heart rate at blood lactate levels of 1.5 mmol·L<sup>-1</sup> (HR<sub>lac</sub>) and 4 mmol·L<sup>-1</sup> (HR<sub>OBLA</sub>) as well as velocity at blood lactate levels of 1.5 mmol·L<sup>-1</sup> (v<sub>lac</sub>) and 4 mmol·L<sup>-1</sup> (v<sub>OBLA</sub>) (Stagno, Thatcher and Van Someren, 2007). Similar to Edwards TRIMP model, 5 heart rate zones were used; however, in this model, they were based around the findings for

$HR_{lac}$  and  $HR_{OBLA}$ . Specifically, zones 2 and 4 were centered around  $HR_{lac}$  and  $HR_{OBLA}$ , respectively, and the remaining zones were fit around these, with similar widths (Stagno, Thatcher and Van Someren, 2007). In addition, as opposed to using arbitrary weights of 1-5 for the zones, an exponential line of best fit was calculated from the data collected on blood lactate and fractional elevation of exercising heart rate, and this curve was used to determine zone weights (Stagno, Thatcher and Van Someren, 2007). The zones and their weighting factors are as follows.

*Table 2.1: Modified Team TRIMP Zones and Weightings*

<b>Zone</b>	<b>% Max HR</b>	<b>Weighting</b>
<b>1</b>	65-71	1.25
<b>2</b>	72-78	1.71
<b>3</b>	79-85	2.54
<b>4</b>	86-92	3.61
<b>5</b>	93-100	5.16

The researchers in this study found that the mean weekly modified TRIMP score for the athletes was  $826 \pm 123$ , and the average modified TRIMP values for matches and training were  $355 \pm 60$  and  $236 \pm 41$ , respectively (Stagno, Thatcher and Van Someren, 2007). Furthermore, mean weekly training load was correlated with changes in maximum volume of oxygen consumption ( $VO_2 \max$ ) ( $r=0.80$ ) and  $v_{OBLA}$ , the velocity at a blood lactate concentration of  $4 \text{ mmol} \cdot \text{L}^{-1}$  during the submaximal fitness test described above ( $r=0.71$ ). These results suggest that Stagno et al.'s (2007) modified TRIMP is a valid and useful method of monitoring internal training load, as it is predictive of fitness changes. However, despite these findings, there are still several limitations to be considered. Firstly, the sample size was small (8 participants) and only included male athletes, so the heart rate zones and weightings may not be appropriate for female athletes, or even for other groups of male athletes. In addition, the zones and weightings were based on averages across the 8 individuals as opposed to being calculated for each individual separately, so this model may be more accurate for some athletes than others.

In order to combat the limitations of the modified TRIMP method, a new, fully individualized method of monitoring TRIMP, called iTRIMP, has been introduced. Calculating iTRIMP follows much of the same procedure as the Stagno et. al study (2007), except, instead of using averages, each individual's data are analyzed separately to create a fully individualized equation for training load (Malone and Collins, 2016). Manzi et al.

originally described and tested this procedure in recreational distance runners (2009). In the study, each athlete performed a submaximal treadmill test which consisted of 4-5 four-minute stages with a one-minute rest between stages. The beginning speed was 10 km·h<sup>-1</sup> and speed increased by 2 km·h<sup>-1</sup> for each subsequent stage. Heart rate was continually monitored throughout the test and earlobe capillary blood lactate samples were taken at the end of each stage. Heart rate reserve  $\left( \frac{HR_{ex}-HR_{rest}}{HR_{max}-HR_{rest}} \right)$  was then plotted against blood lactate to produce individualized blood lactate curves (Manzi *et al.*, 2009). As opposed to designing zones and weights from the curve as Stagno *et al.* did, this equation was then used to determine the weighting for each individual heart rate measurement and TRIMP was calculated by summing the weighted score for each heart rate data point recorded during a session (Manzi *et al.*, 2009). Athletes were monitored for an 8-week period and results indicated that iTRIMP was strongly correlated with 5000 m running time ( $r=-0.77$ ) and 10000 m running time ( $r=-0.82$ ) (Manzi *et al.*, 2009). However, the implications of these results for team-sport athletes are limited, as endurance running lacks the intermittent nature of team-sports.

In addition to Manzi *et al.*'s study (2009) on distance runners, iTRIMP has also been used to monitor internal training load in intermittent team-sport athletes with similar results. In 20 hurling players, iTRIMP, monitored over 8 weeks, was shown to be strongly correlated with VO<sub>2</sub> max ( $r=0.77$ ) (Malone and Collins, 2016). Similarly, in 14 professional youth football players, iTRIMP monitored over an 8-week preseason was strongly correlated with improvements in VO<sub>2</sub> max ( $r=0.77$ ) (Manzi *et al.*, 2013). On the other hand, a different study on professional youth football players found only a moderate correlation ( $r=0.67$ ) between mean weekly iTRIMP and percent change in velocity at blood lactate concentrations of 2 mmol·L<sup>-1</sup> during a submaximal treadmill test (Akubat *et al.*, 2012). However, the sample size was small (nine participants) and the study only lasted six weeks, both of which could have contributed to the weaker correlation (Akubat *et al.*, 2012). Overall, these studies suggest that iTRIMP is an effective method of monitoring internal training load and predicting fitness changes in team-sport athletes. However, no study to date has investigated iTRIMP in hockey athletes.

### 2.3.3 Heart Rate Monitoring in Hockey

As in many other team sports, monitoring heart rate has become fairly common in hockey, particularly when research is being conducted. Heart rate has been measured across a

variety of different populations of hockey athletes and findings have mostly been reported in terms of average heart rate during competition. Table 2.2 summarizes these findings.

*Table 2.2: Average Heart Rate in Hockey Competition*

Author(s)	Date	# Subj	M/F	Level	Average Heart Rate (either %HR <sub>max</sub> or bpm)			
					Team	Defense	Midfield	Forward
Lythe	2008	18	M	International	85.5±2.9	84.4±2.5	86.5±2.6	85.6±3.7
Sell & Ledesma	2016	10	F	University	87.4±3.5	86.9±7.4	90.0±3.8	84.7±5.0
Vescovi	2016	44	F	International	89	90±4	88±5	90±3
McGuinness et al.	2017	38	F	International	85±5	86±2	87±2	85±12
Macutkiewicz & Sunderland	2011	25	F	International	172±8	172±7	168±9	175±7
Boran	2012	36	F	Amateur	165±13	165±17	169±8	162±15

Although these studies are somewhat varied in their results, together they provide an overview of average heart rate during competition. It is important to note that due to the use of rolling substitutions in hockey, these averages are calculated from time on the pitch rather than a full game analysis. From the table, it is clear that, in some cases, there are differences between the average heart rate profiles across positions, indicating that playing in different positions may vary the physiological stress of hockey. However, there is no one position that consistently had the highest or lowest average heart rate across the studies. This lack of consistency is likely caused by tactical differences and varied playing styles between teams. Furthermore, mean percent of maximum heart rate is highest in the Sell & Ledesma and Vescovi studies. Interestingly, these studies were both performed on younger populations, specifically university athletes (age 18-22) and junior international athletes (age ~16-21). This finding suggest that average heart rate may be slightly higher in elite young adult populations, perhaps due to decreased technical proficiency and physical fitness.

Although considering average heart rate can be useful in understanding the physical demands of hockey competition, the potential interpretations of these findings are limited due to the intermittent nature of hockey. As a result, some studies have further broken up heart rate data into time spent in heart rate zones; however, the cutoffs between the zones vary making these findings difficult to compare (Lythe, 2008; Sell and Ledesma, 2016; McGuinness *et al.*, 2017). To date, there have only been two studies published that evaluate

TRIMP in hockey. The first of these studies was the Stagno study discussed above (Stagno, Thatcher and Van Someren, 2007). The only other study that has evaluated TRIMP in hockey was Vescovi's study (2016) of the Canadian U17 and U21 national teams. This study used the weightings established in Stagno et al.'s model, but the zones were slightly different (60%-70%, 70-80%, 80-85%, 85-90%, 90-100%), making a true comparison between the studies nearly impossible (Vescovi, 2016). However, this study did find a statistically significant difference in TRIMP values between forwards ( $242 \pm 64$ ) and defenders ( $446 \pm 100$ ) ( $p < 0.001$ ) and between midfielders ( $291 \pm 109$ ) and defenders ( $p = 0.011$ ) during competition (Vescovi, 2016). However, these differences may be explained by the fact that defenders spent more time on the field ( $51.0 \pm 10.3$  min) compared to midfielders ( $42.1 \pm 11.8$  minutes) and forwards ( $29.8 \pm 7.8$  minutes). Overall, the lack of studies on TRIMP in hockey players indicates that this is an area where further research is needed. As TRIMP and iTRIMP have been shown to be very effective measures of monitoring internal training load and predicting fitness changes in other sports, it is likely that these measures could be applied to hockey and used to inform coaching decisions. However, more research is needed to determine the effectiveness of Stagno et al.'s modified team TRIMP in female hockey populations as well as iTRIMP in both male and female hockey populations.

#### 2.4 Global Positioning System (GPS) Data

Unlike RPE and TRIMP, which are both measures of internal training load, GPS data provide information on the overall physical work output, or external training load, of athletes. Monitoring external training load, which is now almost exclusively performed using GPS trackers and accelerometers, began before these devices were invented. Early studies on football date back into the 1970s and relied on time-consuming video analysis techniques of charting athlete movement (Spencer *et al.*, 2004). This method of athlete tracking, often referred to as time-motion analysis, requires cameras that have been set up either to film the entire playing surface or to follow an individual player (Spencer *et al.*, 2004). Experienced operators then analyze the film, watching individual players and coding their movements (Spencer *et al.*, 2004). Software such as SIMI Scout, in which the playing surface is calibrated to a two-dimensional coordinate plane, has been developed to assist with the notational process, and studies have been performed using time motion analysis in hockey as recently as 2013 (Liu *et al.*, 2013). However, as GPS technology has developed, it has mostly replaced time-motion analysis since GPS can instantly produce variables that take up to 8 hours to determine using video analysis, multiple athletes can be tracked simultaneously,



and no camera set-up is required (Scott, Scott and Kelly, 2016). As hockey is not frequently played indoors or in very large stadiums where extremely advanced automated video analysis systems are more commonly utilized, GPS tracking is the primary method of monitoring external training load in hockey athletes.

GPS is a navigational system that was first created by the United States Department of Defense for military applications (Scott, Scott and Kelly, 2016). It is based around 27 satellites each equipped with an atomic clock that sends information, at the speed of light, to GPS receivers (Macleod *et al.*, 2009). GPS receivers determine the lag time of the satellite's clock signal and use this to determine distance (Scott, Scott and Kelly, 2016). With a minimum of four satellite signals, a GPS receiver can calculate exact location and altitude (Scott, Scott and Kelly, 2016). Originally restricted to military use, the US military removed restrictions on civilian GPS use in the 1980s, but introduced a deliberate error which significantly reduced its accuracy (Macleod *et al.*, 2009). It was not until 2000 that the deliberate error was reduced, greatly increasing non-military GPS applications (Macleod *et al.*, 2009). GPS was first used to track athletes in 1997, and, since the error has been removed and portable, reasonably priced monitors have been developed, GPS tracking has become a key component of many athlete monitoring systems (Cummins *et al.*, 2013). In sport, GPS units are categorized by the number of times they collect data each second (Scott, Scott and Kelly, 2016). The first units were 1 Hz (one data point per second), but now 5Hz, 10 Hz, and, very recently, even 15 Hz devices have been developed (Scott, Scott and Kelly, 2016). In addition, many GPS units also contain a triaxial accelerometer which can measure acceleration in all three planes (Scott, Scott and Kelly, 2016).

#### 2.4.1 Validity of GPS Data

Although GPS is now accepted and commonly used for monitoring team sport athletes, the validity of GPS technology has been continually questioned throughout its development. One Hz GPS units were the first to be used in team sports, and, as they only collect data once per second and team sports involve lots of rapid movements and changes of direction, people were unsure if these units could capture enough information to be accurate (Scott, Scott and Kelly, 2016). For example, if an individual were to move a meter to the right and then return to their initial position within one second, the unit would record no movement. Over the course of a game, particularly when individuals are moving at high speeds, these small errors could add up significantly. A 2009 study investigated the validity of a 1 Hz GPS unit for measuring speed and total distance in a circuit designed, based on

time-motion analysis, to stimulate player movement during a hockey match (Macleod *et al.*, 2009). The exact length of the circuit, which included various shuttles, turns, and pace changes, was measured using a trundle wheel and timing gates were set up to determine speed (Macleod *et al.*, 2009). The results of the nine participants indicated that 1 Hz devices are valid methods of measuring total distance and mean speed, as the GPS data recorded, on average, a total distance of 6820.5 m compared with an actual distance of 6218.0 m and correctly recorded a mean speed of 7.0 km·h<sup>-1</sup> (Macleod *et al.*, 2009). However, the limitations lay within some of the shuttles, which required high speed running accompanied by changes of direction. In each of the four shuttles, the mean distance measured by the GPS was significantly different than the actual distance ( $p < 0.01$ ), and there was a significant difference in the GPS reported and actual speed during the straight-line sprint shuttle (Macleod *et al.*, 2009). Overall, a review study found that although accurate for measuring total distance, when used to monitor movements at higher speeds, particularly over shorter distances (< 40 m), 1 Hz monitors fail to achieve an acceptable (<10% error) level of validity (Scott, Scott and Kelly, 2016). As team sports involve many short, high-intensity movements, this calls into question the validity 1 Hz GPS devices for monitoring team sports.

Overall, studies suggest that 10 Hz GPS units are the most accurate and can consistently provide data with good levels of validity and reliability (<5% error) in team sport athletes (Johnston *et al.*, 2014; Scott, Scott and Kelly, 2016). Although 5 Hz GPS units are an improvement on the 1 Hz GPS models, they have similar limitations (Scott, Scott and Kelly, 2016). Studies on 5 Hz models reported a high level of accuracy for total distance; however, accuracy fell off dramatically during very high speed running and running that involved rapid acceleration from standing (Scott, Scott and Kelly, 2016). In contrast with the 1 Hz and 5 Hz model, 10 Hz GPS units were found to provide accurate measurements at varying speeds and distances, including short sprints (Scott, Scott and Kelly, 2016). In fact, a 2012 study that involved athletes wearing both 5 Hz and 10 Hz GPS units simultaneously found that the 10 Hz model was 2-3 time more accurate than the 5 Hz model at measuring instantaneous velocity (Varley, Fairweather and Aughey, 2012). Specifically, when comparing instantaneous velocity for speeds within ranges of 1-3, 3-5, and 5-8 km·hr<sup>-1</sup>, for over 250 samples per speed range, the average percent bias ranged from -0.5% to 2.4% for 5 Hz models and -0.2% to 0.6% for 10 Hz models (Varley, Fairweather and Aughey, 2012). Considering these findings, one might expect that a 15 Hz GPS would provide further significant improvements in monitoring athlete movement, but this has not been shown to be the case (Scott, Scott and Kelly, 2016). In fact, studies have found that 15 Hz units have no

additional benefit and, in some cases, are worse than 10 Hz models at measuring athlete movement (Scott, Scott and Kelly, 2016). Specifically, a study in which athletes wore both 10 Hz and 15 Hz monitors simultaneously found the 15 Hz monitors to be less accurate at measuring total distance (Johnston *et al.*, 2014). It has been suggested that this decrease in accuracy may be due to the methods used to increase the sampling rate in 15 Hz units, indicating that the technology for 15 Hz units has yet to be perfected (Johnston *et al.*, 2014). However, due to their recent development, the amount of research on these models is very limited. Thus, the current findings suggest that 10 Hz GPS units be used to provide the most valid and reliable information on external training load in team-sport athletes.

#### 2.4.2 Measuring Total Distance in Hockey Competition

Over the past decade there has been a large influx of research focusing on external training load in hockey competition. This research has been performed on a wide range of populations, both male and female, national level and international, with the aim of characterizing the physiological demands of hockey competition. The most commonly reported measure of external training load across all the studies is distance travelled, often separated out by position. This metric is limited in that it provides no information on speed or time, which are both key to understanding the demands of hockey due to its intermittent nature and rolling substitutions. However, examining total distance is a good starting point for understanding the external training load of hockey and how load varies across positions.

*Table 2.3: Total Distance in Hockey Competition*

Author(s)	Date	# subj	Games	M/F	Level	Distance (m)	Defense	Midfield	Forward
Gabbett	2010	14	32	F	N	6600	6643±1618	6931±1882	6154±271
Macutkiewicz & Sunderland	2011	25	13	F	I	5541±1144	6170±977	5626±787	4700±918
Boran	2012	36	1	F	N	6188±781	5896±801	6660±542	6009±796
Vescovi & Frayne	2015	68	1	F	N	6493	6556±1120	6765±1392	6062±1371
Abbott	2016	16	13	F	I	8823±1776*	8056±972*	7534±954*	11965±314*
Vescovi	2016	44	4	F	I	4351	5143±759	4735±1305	3283±842
McGuinness et al.	2017	38	19	F	I	5540±521	5696±530	5555±456	5369±578
Lythe	2008	18	5	M	I	6798±2009	-	-	-

Jennings et al. (b)	2012	15	6	M	I	9776±720*	9453±579*	10160±215*	9819±720*
Jennings et al. (a)	2012	16	8	M	N	8589±623*	-	-	-
Liu et al.	2013	38	1	M	N	7334±877	6671±745	7733±729	7709±720
White & MacFarlane	2013	16	8	M	I	5819	-	-	-
White & MacFarlane	2015	16	8	M	I	5868	-	-	-
Polglaze et al.	2015	24	7	M	I	6095±938	6257±909	6156±1055	5409±689
Sunderland & Edwards	2017	20	17	M	I	6594±1074	8223±456	6811±778	5881±774

All distances in meters.

I: International, N: National

\*Data collected by position, not by individual

Table 2.3 summarizes the findings of total distance covered in hockey competition, separated by the three primary outfield positions. The games column lists how many competitions were analyzed for each of the subjects, thus providing additional information on the sample size. Furthermore, it is important to note that the distances reported in the Abbott and Jennings et al. studies were calculated according to position, as opposed to individual, meaning that the distance values were summed across all athletes who played on the field in a specific position (for example left defender) (Abbott, 2016; Jennings *et al.*, 2012a; 2012b). Although this measurement technique does provide useful information into position-specific distance, it gives little information on the distances covered by individuals since athletes generally do not play for the full duration of a match. Therefore, as distances across individuals are summed, it follows that the distance values by position will be higher than those reported for individuals. Another potential consideration when comparing distance measures across the studies above is whether just time on the pitch or the full game was used to calculate distances (White and MacFarlane, 2013). However, a study comparing time on pitch and full game analyses for distance measures showed that there was little difference (5 m) between the two methods (White and MacFarlane, 2013). This is likely due to the fact that the bench is generally very close in proximity to the field, and players usually remain relatively stationary until they return to the game. Therefore, there is little need to distinguish time on pitch and full games analyses when considering total distance.

Overall, from the data presented above, one can conclude that the average distance travelled by an adult hockey athlete during competition ranges from 5.8-7.3 km for males and 5.5-6.6 km for females. Note that the Vescovi 2016 study has been excluded from these ranges as it incorporated data on youth field hockey athletes, which may be the reason for the lower total distance findings. From these ranges it appears that female hockey athletes may cover, on average, slightly less distance per game than male athletes; however, it is unclear whether this difference is significant. Furthermore, from these studies it appears that there is no clear relationship between the level of hockey competition and the total distance covered. This is in contrast with the findings of Jennings *et al.*, which compared distance travelled by players in the Australian hockey league and players on the Australian national team and found that the international athletes covered greater total distances than national level athletes (Jennings *et al.*, 2012b). Finally, it is challenging to draw any conclusions on the differences between total distance across the three positions, as the findings vary across the studies. This is likely due to different playing and substitutions styles across various teams.

#### 2.4.3 Measuring Distance across Speed Zones in Hockey Competition

In addition to measuring total distance, many of the studies on external training load during hockey competition have examined the distance travelled or percent of time spent in distinct speed zones. As hockey is intermittent, this type of analysis provides more information on the intensity at which athletes are working and is often more valuable for coaches (Abbott, 2016). In most cases, the speed zones used for analysis are based around locomotor categories, such as walking, jogging, striding, and sprinting (Dwyer and Gabbett, 2012). However, the definitions for these actions vary dramatically, causing cutoffs to differ and making comparison almost impossible. In response to this problem, Dwyer and Gabbett suggested that velocity zones be standardized and that these standardized categories be based on sport-specific movement profiles (Dwyer and Gabbett, 2012). After analyzing data from 5 male and female national-level hockey players across 5 games, the following cutoffs ( $\text{km}\cdot\text{h}^{-1}$ ) were recommended for use in hockey (Dwyer and Gabbett, 2012).

*Table 2.4: Gabbett's Recommended Speed Zones*

( $\text{km}\cdot\text{h}^{-1}$ )	Stand	Walk	Jog	Run	Sprint
<b>Male</b>	0-0.4	0.5-6.1	6.2-11.5	11.6-20.2	>20.2
<b>Female</b>	0-0.4	0.5-6.1	6.2-13.0	13.1-19.1	>19.1

Although the idea of standardizing zone cutoffs is certainly an important one, there is insufficient evidence to suggest that these zones should be adopted as the standard for hockey. Specifically, the sample size was very small, with only five games from five athletes of each sex included in the analysis (Dwyer and Gabbett, 2012). All athletes participated in the same league and no international matches were included, suggesting that this convenience sample may not be representative of the larger hockey community (Dwyer and Gabbett, 2012). Finally, the GPS units used during this study were 1 Hz models, which, as discussed above, have been shown to be inaccurate when measuring high speed running over short distances (Dwyer and Gabbett, 2012; Scott, Scott and Kelly, 2016). Another method of determining velocity zones is using individualized cutoffs based on an athlete's maximum speed (Gabbett, 2015). As may be expected, using individualized zones has been shown to increase the amount of work classified as high speed running in slow players and decrease it in fast players (Gabbett, 2015). However, individualized speed zones are limited by the fact that an athlete's maximum speed may change over time.

A table summarizing distance across speed zones in hockey athletes is included in Appendix A. Before drawing conclusions from this table, some limitations should be noted. Specifically, the Liu et al. (2013) study was performed using video analysis as opposed to GPS, and the Jennings et al. (2012b) study was performed over the course of a tournament involving 6 games played within 9 days. Additionally, some studies grouped players in different positional categories (for example distinguishing halfbacks and screens), so some adjustments have been made to best group the data into the three primary outfield positions. From these studies it is clear that the majority of distance covered in hockey is at a low to moderate intensity, and less distance is covered at very high intensities. This conclusion may seem in contrast to the results on heart rate during hockey competition which indicate that team average heart rate ranges from 85-89% of maximum heart rate, suggesting that hockey is performed at a very high intensity (Lythe, 2008; Sell and Ledesma, 2016; Vescovi, 2016; McGuinness *et al.*, 2017). However, when considered together these results indicate that although hockey athletes cover a large percent of their total distance at relatively low intensities, the pattern of high intensity actions interspersed among low intensity movements is challenging from a physiological perspective, thus resulting in a relatively high average heart rate. Despite the different speed zones, it appears that forwards generally tend to cover greater distances at very high speeds than defenders or midfielders. This suggests that position-specific training may be appropriate to best prepare athletes for the physiological demands of competition. Finally, the inability to easily compare the findings of these studies due to the

varying speed zones provides further evidence on the need for standardized velocity definitions.

#### 2.4.4 Other Methods of Measuring External Load

In addition to measuring total distance and distance in speed zones, other methods, such as player load and workrate, have been used to quantify external training load in hockey athletes. Unlike GPS measures that track movement in the x-y plane, player load is derived from triaxial accelerometers and represents the total accelerations of the body in all three planes (Boyd, Ball and Aughey, 2013). Player load is usually calculated by taking the square root of the sum of the squared accelerations in the x, y, and z directions, all over 100; however, various companies that sell GPS monitors have slightly different proprietary algorithms used to calculate this value (Boyd, Ball and Aughey, 2013; Abbott, 2016). In all cases though, player load is a numerical score, in arbitrary units, that represents acceleration and deceleration in all dimensions (Abbott, 2016). Some of the benefits of player load include that it can be used as an expression of external training load when GPS data are not available, particularly in indoor sports (Boyd, Ball and Aughey, 2013). Furthermore, player load has been shown to have a strong relationship with Edward's TRIMP ( $r=0.80$ ) and sRPE ( $r=0.84$ ) (Scott *et al.*, 2013a).

Studies on player load in hockey are very limited, as GPS-based measures are more commonly used to determine external training load. However, two studies have reported average player load during competition with similar results. The first study, performed on 16 male international hockey players, reported an average player load of  $631 \pm 30$  (White and Macfarlane, 2015a). Similarly, the other study, also on male international hockey players, found the average player load to be  $617 \pm 106$  (Polglaze *et al.*, 2015). Player load was found to be higher in defenders,  $649 \pm 114$ , than forwards,  $577 \pm 67$ , but this difference was not significant (Polglaze *et al.*, 2015). No study has analyzed the relationship between player load and fitness changes or measures of internal training load in hockey athletes. The lack of data available in this area indicates that player load may require further investigation; however, the benefit of calculating player load in addition to other GPS measures such as total distance has been questioned (Polglaze *et al.*, 2015). Specifically, player load has been shown to be very highly correlated ( $r=0.868$ ) with total distance in hockey (Polglaze *et al.*, 2015). As hockey is a non-contact sport, most of player load is accumulated through locomotor activities such as running, rather than from contact with other players (Polglaze *et al.*, 2015). Therefore, it has been suggested that little additional information is gained from

player load when total distance is already being reported, as player load mostly expresses duplicate information (Polglaze *et al.*, 2015).

Workrate, expressed in meters per minute, is another method of analyzing total distance that takes into consideration individual players' time on the pitch. Due to the rolling substitutions in hockey, players rarely play for the full seventy minutes. In fact, several studies have reported average player minutes during competition, as shown in Table 2.5 below.

*Table 2.5: Minutes per Match in Competition*

Author(s)	Date	M/F	Team	Defense	Midfield	Forward
Macutkiewicz & Sunderland	2011	F	48±4	56±11	50±10	38±7
Abbott	2016	F	47.6	57.5±11.4	41.4±8.3	38.3±1.3
Vescovi	2016	F	40.3	51.0±10.3	42.1±11.8	29.8±7.8
McGuinness et al.	2017	F	44±7	50±8	43±5	41±6
Lythe	2008	M	51.9±17.8			
White & MacFarlane	2013	M	48			
Polgaze et al.	2015	M	46.8±7.3	52.1±7.2	45.2±7.2	42.0±5.4
Sunderland & Edwards	2016	M	48.6±10.9			

All times are expressed in minutes, and all competition was at the international level.

From these studies, one can see that the average playing time on a team is generally between 46 and 48 minutes or 65.7-68.5% of total match time; however, average playing time ranges from 40.3 to 51.9 minutes (57.6% - 74.1%). Furthermore, playing time is noticeably different between the positions with forwards generally playing the fewest minutes and defenders the most. Additionally, the relatively large standard deviations values, as high as 17.8 minutes in the Lythe study, indicate that playing time varies greatly between individuals, sometimes even within the same position. This variation in playing time highlights the importance of using relative measures such as workrate, in addition to absolute measures of total distance, as some players will accumulate additional distance as a result of an increased time on the pitch, rather than an increased intensity level. Therefore, workrate takes the quotient of total distance and minutes played to determine an average speed value that can be compared across players, regardless of minutes played (White and MacFarlane, 2013).



Several studies have reported findings on athlete workrate during hockey competition.

*Table 2.6: Workrate in Competition*

Author(s)	Date	# subj	Games	M/F	Level	Team	Defens e	Midfiel d	Forwar d
Vescovi & Frayne	2015	68	1	F	N	106	98±11	109±11	110±11
Abbott	2016	16	13	F	I	120±6	107±6	125±11	126±4
Vescovi	2016	44	4	F	I	110	103±9	113±6	111±6
McGuinness et al	2017	38	19	F	I	126±23	114±7	129±5	131±10
White & MacFarlane	2013	16	8	M	I	124			
Polgaze et al	2015	24	7	M	I	131±11	120±8	136±10	129±9

All workrates are expressed in meters per minute on the field. I: International, N: National

From these studies it appears that workrate is higher in international hockey competition than in national or junior international (Vescovi, 2016) competition. Furthermore, workrate is higher in midfielders and forwards than in defenders, and this difference has been shown to be significant ( $p < 0.05$ ) in several studies (McGuinness *et al.*, 2017; Abbott, 2016; Boyd, Ball and Aughey, 2013). This result is linked to the previous finding that defenders generally play more minutes than midfielders and forwards, suggesting that with longer rotations and less rest, defenders are unable to maintain the same workrate as players in other positions. This information can be used to design appropriate training and conditioning programs for each position (Abbott, 2016). It can also be beneficial to compare workrates across a team's games to monitor when individuals or the team as a whole varies from their normal profile, perhaps due to motivation, opposition, or fatigue (White and Macfarlane, 2015b).

#### 2.4.5 Comparisons Across Halves of Hockey Competition

As discussed above, there are many different ways to monitor external training load in hockey competition. Total distance, distance in various speed zones, and workrate all provide important information about an athlete's physical performance. However, in all the previously discussed examples, these metrics were considered over a game as a whole rather

than within a single game. As opposed to examining entire matches, comparing external training load across the two halves of a match provides information on whether performance is being maintained, increasing or dropping off (Abbott, 2016). Ideally, coaches aim to use rolling substitutions as well as appropriate conditioning in training to ensure that athletes are able to maintain the same level of high intensity during both halves of competition (Abbott, 2016). However, some studies have found that athletes' total distance and workrate are significantly different ( $p < 0.05$ ) in the first half versus the second half of competition, with the second half always being the less intense of the two (Boran, 2012; Liu *et al.*, 2013; Vescovi and Frayne, 2015). This suggests that accumulated fatigue in the second half, perhaps due to poor conditioning or substitution strategies, may be resulting in decreased performance in some hockey populations (Vescovi and Frayne, 2015).

*Table 2.7: Differences in External Training Load Between Halves*

I: International, N: National

Authors	Date	# subj	Games	M/F	Level	Results
Spencer et al.	2004	14	1	M	I	No significant difference in motion categories ( $p > 0.05$ )
Lythe	2008	18	5	M	I	Substantial difference in total distance ( $p = 0.06$ )
Boran	2012	36	1	F	N	Significant difference in total distance ( $p = 0.042$ )
Liu et al.	2013	38	1	M	N	Significant difference in workrate ( $\text{m} \cdot \text{min}^{-1}$ ) ( $p < 0.001$ )
Vescovi & Frayne	2015	68	1	F	N	Significant 7-9% difference in total distance ( $p < 0.001$ )
Abbott	2016	16	13	F	I	No significant difference in the percent of distance travelled in various speed zones ( $p > 0.10$ )
McGuinness et al.	2017	38	19	F	I	No significant difference in total distance ( $p = 0.6$ ) or workrate ( $\text{m} \cdot \text{min}^{-1}$ ) ( $p = 0.5$ )

Table 2.7 summarizes the results of studies comparing the external load of athletes across halves of a game. In all cases where significant differences were found, the second half had the lower workload of the two, likely due to fatigue (Boran, 2012; Liu *et al.*, 2013; Vescovi and Frayne, 2015). As can be seen, the results are mixed, with some studies finding significant differences in total distance and workload and others finding no significance. However, on closer inspection, one can see that significant differences in external load between halves were only found in studies on athletes below the international level, with no significant differences being observed in studies taking place on international athletes. The

only slight exception to this is the Lythe study, which took place on international male hockey players and found a substantial, but technically not significant difference ( $p=0.06$ ), in total distance across the two halves of the game (Lythe, 2008). However, care should be taken when interpreting Lythe's findings, as the five games that were examined during this study took place within 8 days, as part of a tournament (Lythe, 2008). Thus, particularly by the final games of the tournament, athletes may have been experiencing accumulated fatigue, causing a greater reduction in total distance during the second half of matches than may have normally occurred if there was to be more rest between matches. Overall, these findings indicate that international athletes, unlike lower level athletes, are able to maintain their external workload over the course of a match, perhaps due to better physical conditioning or substitution strategies. However, these studies are not representative of all hockey populations, so more research is needed to determine if external training load is only maintained over both halves of a match in international hockey athletes and to determine if training intensity or other factors are contributing to this.

#### 2.4.6 Measuring External Load in Hockey Training

In addition to the research performed on GPS data in hockey competition, several studies have investigated external training load in training environments (Polglaze *et al.*, 2015; Gabbett, 2010; White and Macfarlane, 2015b). In team sports, the most effective form of training has been shown to be that which best mirrors the movement patterns and intensity of competition (Abbott, 2016; Liu *et al.*, 2013). Therefore, the goal of these research studies has been to determine if training drills are appropriately mirroring the physiological stresses that athletes face in games scenarios. When comparing the demands of training and games, it is important to focus on the portions of training designed to mirror game environments. Specifically, technical skill-based training such as hitting practice or repeated set-play rehearsals such as penalty corners should not be included, as these are relatively stationary in nature. Unlike skill-based training, small-sided games are designed to mirror game situations. Although there are countless variations, small sided games are always played in a smaller space with a reduced number of players, often under unique rules and constraints (Polglaze *et al.*, 2015). These types of training drills have become very common, as they can be used for conditioning, they focus on a specific concept from match-play, and the reduced numbers allow players to spend more time on the ball (Polglaze *et al.*, 2015).

Several studies have compared the intensity of small sided games and matches with mixed results. A 2010 study of 14 elite female hockey players examined the amount of time

spent at low ( $0-1 \text{ m}\cdot\text{s}^{-1}$ ), moderate ( $1-3$  and  $3-5 \text{ m}\cdot\text{s}^{-1}$ ), and high intensity ( $5-7$  and  $>7 \text{ m}\cdot\text{s}^{-1}$ ) in both training and competition (Gabbett, 2010). The findings suggested that game-based training sessions may not accurately mirror the demands of competition as players spent significantly more time at low intensities and significantly less time at moderate and high intensities in training than in games ( $p<0.05$ ) (Gabbett, 2010). Similarly, a study on 24 international male hockey players found that workrate (meters per minute) and player load were both significantly lower in training,  $p=0.001$  and  $p=0.043$ , respectively (Polglaze *et al.*, 2015). However, a 2015 study on sixteen international male hockey players found that workrate was not significantly different between competition ( $78\pm2 \text{ m}\cdot\text{min}^{-1}$ ) and small side games ( $74\pm3 \text{ m}\cdot\text{min}^{-1}$ ) ( $p>0.05$ ) (White and Macfarlane, 2015a). This study also examined the percentage of total time spent sprinting and running at a high intensity and found these to be the same in both training and small sided games (White and Macfarlane, 2015a). From these mixed findings, it appears that small sided games can appropriately mirror the physical demands of competition, but that this is not always the case. Therefore, it is important to monitor training load during small sided games to ensure that they are being performed at an appropriate intensity.

### 2.5 Combining Internal and External Training Load Measures

As tracking devices have become more accessible, many teams have begun collecting data on both internal and external training load measures. Several studies have compared internal and external load by examining the correlations between them, and a summary of the correlation coefficients is included in Table 2.8 below. Specifically, a study of fifteen male professional football players found that total distance (TD) and player load (PL) were very significantly correlated with Banister's TRIMP (TD:  $r=0.73$ , PL:  $r=0.73$ ), Edward's TRIMP (TD:  $r=0.78$ , PL:  $r=0.80$ ), and sRPE (TD:  $r=0.80$ , PL:  $r=0.84$ ) (Scott *et al.*, 2013a). Additionally, a study of fourteen international wheelchair rugby players found a very large correlation of both Banister's TRIMP and Edward's TRIMP with total distance ( $r>0.80$ ) (William *et al.*, 2015). However, the relationship between sRPE and total distance was weaker ( $r=0.59$ ) (William *et al.*, 2015). In contrast with these findings, a study of 8 semi-professional male basketball players found weaker correlations between internal and external training load measures (Scanlan *et al.*, 2014). Specifically, there was only a weak moderate correlation between player load and Banister's TRIMP ( $r=0.38$ ) and sRPE ( $r=0.49$ ), and only a slightly larger correlation was found when using Edward's TRIMP ( $r=0.61$ ) (Scanlan *et al.*,

2014). However, the sample size of 8 individuals was small, so further studies would be needed to confirm these findings (Scanlan *et al.*, 2014).

*Table 2.8: Correlation Coefficients between Internal and External Training Load Measures*

	Total Distance	Player Load
Banister's TRIMP	0.739 <sup>(1)</sup> , 0.81 <sup>(2)</sup>	0.73 <sup>(1)</sup> , 0.38 <sup>(3)</sup>
Edward's TRIMP	0.78 <sup>(1)</sup> , 0.84 <sup>(2)</sup>	0.80 <sup>(1)</sup> , 0.61 <sup>(3)</sup>
sRPE	0.81 <sup>(1)</sup> , 0.59 <sup>(2)</sup>	0.84 <sup>(1)</sup> , 0.49 <sup>(3)</sup>

(1) – Scott *et al.*, 2013a (2) - William *et al.*, 2015 (3) – Scanlan *et al.* 2014

Shifting the focus to hockey, although some studies have reported findings on both internal and external training load measures, no study has investigated the relationship between the two. Analyzing the correlations between internal and external training load provides useful information because the technology and expertise required to measure both internal and external load may not be available to all teams. Therefore, understanding the relationship between these measures can be useful in cases where it is only possible to make one measurement. However, it is important to remember that external and internal training load measures are distinct constructs, and, as such, it is important not to assume a linear dose-response relationship between the two (Scanlan *et al.*, 2014).

Instead of only examining correlations between internal and external training load, recent research has gone further to investigate what can be learned from the relationship between the two. As individuals can perform an identical external load but have very different internal responses due to fitness and fatigue, among other factors, it has been suggested that the relationship between internal and external load may be useful in tracking fatigue, fitness status, and player performance (Halsen, 2014; Torreno *et al.*, 2016). In order to track the relationship between internal and external load, several recent studies have examined the ratio between internal and external measures. This ratio has been termed the index of performance efficiency, or effindex, as it measures how efficiently the body is working to produce a given output (Torreno *et al.*, 2016). Effindex is most commonly

calculated by taking the quotient of workrate in meters per minute and mean percent of maximum heart rate, thus incorporating mean speed and cardiovascular stress into a single variable. A 2014 study of 30 male professional football players found effindex to be 1.4 in competition, with significant differences ( $p < 0.05$ ) between defenders and other playing positions (Arrones *et al.*, 2014). Similarly, a study of 26 professional male football athletes found effindex to be 1.3 with substantial differences between positions (Torreno *et al.*, 2016). Furthermore, in all positions except strikers, effindex substantially decreased from the first half to the second, suggesting increasing levels of fatigue affecting efficiency in the second half (Torreno *et al.*, 2016). The consistency of effindex in strikers over the course of the match suggests that these athletes were able to recover enough during the match to maintain their level of efficiency. Finally, another study, again on male football players, evaluated effindex by taking the ratio of total distance (TD) to iTRIMP in a controlled training environment (Akubat, Barrett and Abt, 2014). The goal of this study was to evaluate if the distance to iTRIMP ratio could indicate fitness, but the findings showed that TD:iTRIMP had only a moderate correlation with the velocity at lactate threshold ( $r = 0.69$ ) and a weak correlation with velocity at the onset of blood lactate accumulation ( $r = 0.58$ ) (Akubat, Barrett and Abt, 2014). Thus, even when used in a highly controlled training environment, such as the circuits performed in the study, the results indicated that TD: iTRIMP was not a very accurate indicator of fitness (Akubat, Barrett and Abt, 2014).

No study to date has investigated effindex in hockey. Due to the intermittent nature of hockey, the range of styles and opposition, and the rolling substitutions, effindex could be a very useful measure of athlete performance in hockey competition. A 2015 study of elite domestic hockey competition in Scotland found that total distance was significantly correlated with opponent ranking ( $r = 0.71$ ) (White and Macfarlane, 2015b). Therefore, opposition can significantly affect external training load, which may confound findings when simply comparing external load across matches (White and Macfarlane, 2015b). Additionally, several stylistic choices, such as variations in pressing style or attacking tactics, as well as the frequency of penalty corners, which interrupt the flow of the game, can affect the work required of athletes in a competition. Thus, effindex could be a very useful measure in hockey, as it should not be as affected by exterior factors, since a decrease in external workload would likely correspond to a decrease in internal load. Therefore, effindex could decrease the impact of outside factors on training load and provide a more normalized measure for comparison across competitions and for tracking fatigue. In addition, the rolling substitutions in hockey provides natural segments within a game for examining

effindex. Specifically, effindex could be calculated for each stint that an athlete is on the pitch to evaluate if players are becoming significantly more fatigued and less efficient over the course of a match. This information can be used to adjust substitution patterns and rest times to ensure that athletes are able to maintain a high level of intensity. However, effindex is limited in that environmental conditions may influence scores (Sunderland and Nevill, 2005). Specifically, heart rate has been shown to be significantly higher ( $p < 0.05$ ) when athletes performed hockey skills in the heat ( $30^{\circ}\text{C}$ ) as opposed to moderate conditions ( $19^{\circ}\text{C}$ ), and factors such as high winds may influence external output (Sunderland and Nevill, 2005; Moinat, Fabius and Emanuel, 2018). Thus, when analyzing effindex scores it is important to consider any weather conditions that may have influenced the scores.

Overall, although there has been a great deal of research on hockey in the past decade, several areas have yet to be investigated. Specifically, differential sRPE has yet to be studied in hockey training and competition to determine if this simple, perceptual measure provides accurate information on internal training load. If so, differential sRPE would be a useful starting point for monitoring athletes when other more sophisticated methods are not available. Additionally, although Stagno et al. provided a useful formula for calculating modified TRIMP scores specific to hockey, this procedure has yet to be replicated in female athletes (Stagno, Thatcher and Van Someren, 2007). Even more individualized than Stagno et al.'s modified TRIMP, iTRIMP has been used in other sports to fully personalize training load calculation, but has not been studied in hockey athletes. Furthermore, the results on the effectiveness of small-sided games at mirroring the demands of competition have been contradictory, suggesting that more studies are required. Finally, although there has been a large amount of research examining the external demands of hockey competition, no study has yet linked these findings with internal measures to create effindex scores. This study hopes to investigate these gaps in the literature to provide a more complete picture of internal and external training load measures in hockey training and competition and the relationship between the two.

## **Chapter 3: Methodology**

### 3.1 Methodological Approach

When conducting research, there are several methodological approaches that can be taken, based on one's epistemological assumptions. Although these assumptions are often implicit, one cannot perform research without adopting ontological and epistemological positions (Scotland, 2012). Epistemology is a branch of philosophy concerned with obtaining and evaluating the status of knowledge (Thomas, 2011). Essentially, epistemologists examine how knowledge is created and what it means for something to be known (Scotland, 2012). Closely linked with epistemology is ontology, which is concerned with the nature of reality and what constitutes it (Scotland, 2012). Together one's ontological and epistemological assumptions inform the methodology utilized in research. Therefore, this section will discuss various philosophical approaches and justify the research paradigm adopted in this study.

There are two primary philosophical approaches: positivism and interpretivism. Interpretivism is based on the ontological perspective of relativism and the epistemological perspective of subjectivism (Scotland, 2012). In other words, interpretivists believe that reality is inherently subjective and varies based on the individual, and, as such, knowledge depends on the perspective of the person experiencing it (Scotland, 2012). Therefore, interpretivist research involves investigating phenomena from individuals' perspectives and seeking to understand the participants' reality, taking into consideration intangibles, such as feelings and emotions (David and Sutton, 2011). In terms of sport, interpretivists argue that sport is a social activity involving free will and, therefore, cannot be understood in terms of numerical or causal relationships (Gratton, 2010). Interpretivism is associated with inductive reasoning and qualitative data, as open-ended approaches, such as interviews and focus groups, are often used to seek understanding from the viewpoint of the participants (Gratton, 2010; Scotland, 2012). An advantage of the interpretivism is that its flexible and fluid approach allows the researcher to delve deeper into the experience of the participants to discover explanations and investigate potential unexpected findings, rather than just taking measurements (Bryman, 1984). However, the subjective nature of the information gathered often results in limited generalizability and leads to questions on the credibility and reliability of conclusions.

In contrast to the interpretivist approach, positivism is based on the ontological perspective of realism, which assumes that existence is not related to the knower, and the epistemological perspective of objectivism, which assumes that researchers can objectively



gain absolute knowledge (Scotland, 2012). Positivists trust in the power of human objectivity and reasoning, so they believe that a logical, scientific approach can lead to accurate, generalizable findings (Thomas, 2011). As such, positivists use precise measurements and scientific experiments to develop generalizable theories and laws (Gratton, 2010). During positivist research, research is generally performed from the outside, with little emphasis placed on the beliefs and feelings of individual subjects (Bryman, 1984). From a sports perspective, the positivist approach assumes that the sporting environment is relatively stable, allowing for careful measurement and analysis to result in conclusions that are repeatable and not influenced by the researcher's emotions, beliefs, or biases (Gratton, 2010). Due to the precise nature of the positivist approach, the data collected are usually quantitative, allowing for statistical analysis (Gratton, 2010). Furthermore, as the goal is to test theories and create generalizable conclusions, a deductive approach is taken (David and Sutton, 2011). Some benefits of the positivist approach include its objectivity and ability to draw precise, statistically-validated conclusions. However, positivist research can be limited in its application to real-world settings, as outside factors such as emotions and lived experiences often influence human behavior.

For this study, an objective, positivist approach was taken and qualitative data were collected. As the aim was to investigate methods of measuring training load, and training load is a numerical summary of an athlete's work, a quantitative approach naturally fits with this design. A scientific, positivist approach allowed for precise measurement and quantification of athletes' physical and physiological performance in both training and games, as well as athletes' fitness levels. Furthermore, this precise measurement allowed for detailed statistical analysis to determine the correlation between various measures of training load, as well as which measures best predicted fitness outcomes. Although the data collected were still quantitative in nature, differential RPEs provided training load information from the athletes' perspective, allowing this study to overcome a limitation of the positivist approach without utilizing a mixed-model design. Overall, as this research was inherently quantitative in nature and based upon objective measurement, the epistemological perspective of objectivity was adopted and used to inform the methods.

### 3.2 Study Design

This research study was conducted to investigate the relationship between various methods of measuring internal and external training load in university hockey athletes and to summarize the demands of training and competition. An observational approach and repeated

measures design were utilized in which data were collected during participants' normal hockey training and competition, and training load was measured via differential sRPE, heart rate, and GPS parameters. Additionally, participants performed a submaximal lactate threshold treadmill test at the beginning and end of the study to assess fitness, as measured by velocity at set blood lactate levels.

Four primary training load measures were calculated and compared during this analysis: differential sRPE, training impulse, GPS parameters, and efficiency index. Firstly, a team TRIMP algorithm for female hockey athletes (fTRIMP) was established following the procedure of Stagno, Thatcher, and Van Someren (2007), as well as an individualized TRIMP algorithm for each athlete, as outlined by Manzi et al. (2009). The original team TRIMP, the newly calculated models, and external training load measures were compared with fitness markers, specifically fitness test scores and blood lactate concentration at set velocities, to determine which measure, if any, best predicted fitness changes over the course of the season. Additionally, the correlations between differential sRPE, and heart rate and GPS based measures were investigated to determine if differential sRPE is a valid method of monitoring training load in hockey. Two variations of efficiency index (effindex) were also measured, and changes in efficiency within matches were analyzed. Furthermore, both internal and external training load measures were used to compare the intensity of training drills and competition. Finally, comparisons were made between the demands of hockey competition in this population and previously published results to determine if these results validate previous research or suggest that the demands of British university hockey differ from the demands of other hockey populations.

### 3.3 Participants

Seventeen female hockey athletes from Durham University Hockey Club's women's first team participated in this study. Goalkeepers were excluded due to the relatively stationary nature of their position compared with outfield players. As all participants in this study were university students, participants were young adults. Just prior to the start of data collection, participants completed a six-week preseason training period to ensure proper physical conditioning after returning from a summer holiday during which training was suggested but unsupervised.

Although seventeen participants were included in the study, some participants were not able to complete all aspects of the research. Specifically, due to one participant's trypanophobia, sixteen participants completed the lab-based pretesting protocol used to

determine the new fTRIMP algorithm. Furthermore, several players were dropped to the women's second team meaning that heart rate and GPS data could not be collected due to differences in training schedules, and some athletes missed much of the season due to unforeseeable circumstances, such as injury. Therefore, ten athletes were included in the analysis of the demands of British university hockey and the investigations on the relationship between of various measures training load and fitness outcomes over the course of the season.

*Table 3.1: Participant Characteristics (Mean  $\pm$  Standard Deviation) (Range)*

	Number	Age (y)	Height (cm)	Mass (kg)	BMI (kg/m <sup>2</sup> )
Overall Study	17	20.7 $\pm$ 1.2 (18.1-23.5)	165.8 $\pm$ 3.7 (157.6-171.8)	60.6 $\pm$ 5.4 (51.7-70.6)	22.0 $\pm$ 1.6 (18.7-25.3)
New Team TRIMP Calculations	16	20.3 $\pm$ 1.4 (18.1-23.5)	165.9 $\pm$ 3.9 (157.6-171.8)	60.8 $\pm$ 5.4 (51.7-70.6)	22.1 $\pm$ 1.6 (18.7-25.3)
Effect of Fitness Changes	10	20.6 $\pm$ 1.2 (18.6-23.5)	164.7 $\pm$ 3.1 (157.6-168.6)	59.6 $\pm$ 5.2 (51.7-70.6)	21.9 $\pm$ 1.4 (19.8-25.3)

Details of the study were explained to participants during a team meeting, and participants were given the opportunity to ask questions. A participant information sheet (Appendix B) was also provided which outlined all study details, the risks and benefits of participating, and the protocol for withdrawing. Written informed consent (Appendix C) was obtained from interested athletes. The Durham University School of Applied Social Sciences Ethics Committee approved all protocols and procedures for this study.

### 3.4 Participant testing

Participants in this study performed a submaximal treadmill test (H/P/Cosmos Sports and Medical GmbH, Quasar, Nussdorf-Traunstein, Germany) as well as a maximal on-field fitness test, both described below. Data were collected and analyzed using Minimax S4, 10 Hz GPS units (Catapult Sports, Melbourne, Australia) and Polar Team<sup>2</sup> heart rate monitors (Polar Electro, Kempele, Finland) during participants' regular hockey training and competition.

#### 3.4.1 Pre-testing

Before testing, participants were required to complete a pre-screening questionnaire (Appendix C) on current health and existing injuries in order to minimize the risk of cardiovascular complications and musculoskeletal injuries. This questionnaire was adapted from the Physical Activity Readiness Questionnaire (Humphrey and Lakomy, 2003). Participant age, height, and weight were also recorded, and all participants were familiar with treadmill running.

Participants' resting heart rates were measured, as resting heart rate values were needed for TRIMP calculations. Participants were instructed to sit quietly for at least 5 minutes in a quiet location while wearing a heart rate monitor, and the lowest recorded heart rate during this time was taken as resting heart rate (Manzi *et al.*, 2009).

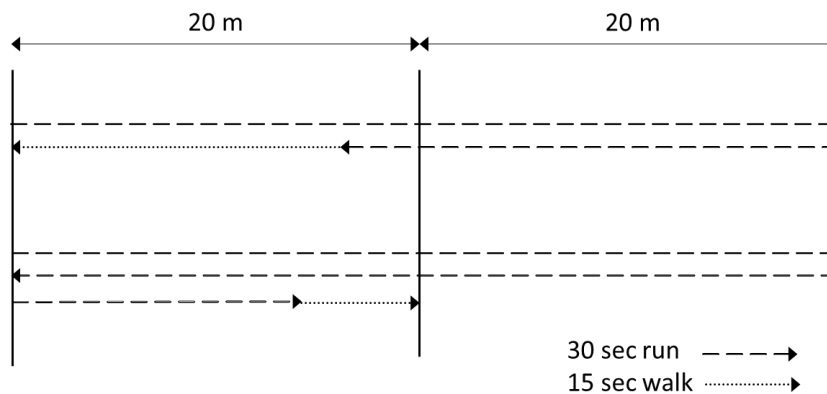
#### 3.4.2 Submaximal Treadmill Test

The participants performed a submaximal treadmill test twice, once at the beginning and once at the conclusion of the study. This test was adapted from published test protocols for calculating team and iTRIMP (Stagno, Thatcher and Van Someren, 2007; Manzi *et al.*, 2009; Malone and Collins, 2016; Akubat *et al.*, 2012; Weaving *et al.*, 2014). To control for extraneous variables, participants were asked to abstain from alcohol and strenuous activity for 24 hours prior to the test. To control for the effects of circadian variation (Weipeng, Michael and Michael, 2011), the two tests for each individual were scheduled to take place at approximately the same time of day. Following the work of Weaving *et al.* (2014), the test consisted of five four-minute running stages with a one-minute rest between stages. The first stage was commenced at a speed of  $7 \text{ km} \cdot \text{hr}^{-1}$  and was increased by  $2 \text{ km} \cdot \text{hr}^{-1}$  for each subsequent stage, resulting in a maximum speed of  $15 \text{ km} \cdot \text{hr}^{-1}$ . The treadmill was set to a gradient of 1% to best replicate outdoor running (Jones and Doust, 1996). Heart rate was monitored using Polar Team<sup>2</sup>, and fingertip capillary blood samples were taken and tested for blood lactate using a handheld lactate analyzer immediately upon the completion of each stage.

#### 3.4.3 30-15 Fitness test

Participants performed an on-field, 30-15 intermittent fitness test to determine maximal heart rate and evaluate fitness levels. This test was previously part of the hockey team's normal fitness assessment program, so participants were familiar with the protocol.

Figure 3.1: 30-15 Intermittent Fitness Test Setup and Example Stages (Buchheit, 2010)



The 30-15 test is a valid and reliable test in which athletes run for 30 seconds followed by 15 seconds of active recovery, at increasing speeds until voluntary exhaustion (Buchheit, 2010). During the test, participants run shuttles across a 40 meter length and speed is regulated by an audio file that beeps when athletes are required to reach certain locations (Buchheit, 2010). A double beep occurs at the end of each 30 second stage, at which point athletes walked to the closest line, where the next stage commences following the 15 second rest. The test began at  $8 \text{ km} \cdot \text{hr}^{-1}$  with the speed increasing by  $0.5 \text{ km} \cdot \text{hr}^{-1}$  each stage until participants reached exhaustion or were no longer able to maintain the speed dictated by the beeps (Buchheit, 2010). The test setup and example stages are illustrated in Figure 3.1. The highest heart rate recorded during the test was taken as  $\text{HR}_{\text{max}}$  for each individual.

#### 3.4.4 Training and Competition Monitoring

Athletes were monitored during training and competition using GPS and heart rate monitors. GPS monitors were worn between the scapulae in the pocket of a specially formulated vest or in the athlete's sports bra, and heart rate monitors were worn across the chest. Monitoring took place during the team's normally scheduled trainings and competitions during the first half of the hockey season (September-December). Although some variations occurred, a typical week consisted of training sessions on Monday from 20:30-22:00 and Friday from 7:30-9:00 as well as matches on Wednesday afternoon and Saturday lunchtime. All data were downloaded to the *Catapult Sprint* and *Polar Team<sup>2</sup>* software packages after each session and then converted to excel files. Heart rate and GPS excel files were then analyzed simultaneously along with RPE scores using code written in Python 3.6 (Appendices E and F). The output for each session was a single excel file detailing all training load measures for each individual with and without phasing for active time on the pitch.

### 3.4.5 Session Rating of Perceived Exertion

Athletes were asked to report ratings of perceived exertion on a modified 100-point Borg scale after each training session and competition, as described by Foster et al. (2001). A 100-point scale was chosen in favor of a 10-point scale to allow for more precise responses. Four separate RPE scores, respiratory, lower body, upper body, and whole body, were collected from each athlete (McLaren *et al.*, 2017). The scale and anchors were explained to the athletes, as well as the importance of providing a global ranking for the entire session. An online

google form was used to collect RPEs for each participant, with athletes being asked to report ‘how exerting you found this session’ in each of the four categories. Athletes were asked not to discuss RPE values with others to reduce the influence of peer pressure. Furthermore, participants were told that there is no ‘correct’ response and that they should avoid changing their behavior just because data are being collected, in order to decrease the influence of the Hawthorne effect (Buckworth, 2002). To calculate sRPE the product of session duration, incorporating only active time, and reported RPE was determined, as outlined by Foster et al. (2001).

*Table 3.2: Rating of Perceived Exertion Scale (Foster et al., 2001, p.111).*

RATING	DESCRIPTOR
0	Rest
10	Very, Very, Easy
20	Easy
30	Moderate
40	Somewhat Hard
50	Hard
60	.
70	Very Hard
80	.
90	.
100	Maximal

## 3.5 Analysis

### 3.5.1 TRIMP calculations

TRIMP was calculated for each participant during all training sessions and matches according to three different algorithms. Two of the algorithms were the same for all athletes, and, as such, are termed team TRIMPs, while the final algorithm involves constants that were distinct for each individual and, as such, is termed individualized TRIMP (iTRIMP). Regardless of the algorithm and terminology, TRIMP for a given session was always calculated for each individual participant based on their unique heart rate data, rather than using average heart rate values from the team as a whole.

The first method used to calculate TRIMP was the modified team TRIMP for hockey described by Stagno, Thatcher, and Van Someren (2007). In this method, five predetermined heart zones were utilized, and the amount of time (in minutes) in each zone was multiplied by the zone's weighting (Stagno, Thatcher and Van Someren, 2007). The sum of the weighted scores across the zones was taken as an individual's score for the session (Stagno, Thatcher and Van Someren, 2007). The zones and weightings were derived from the physiological response of individuals to submaximal exercise; however, only male hockey players were considered in the study (Stagno, Thatcher and Van Someren, 2007).

*Table 3.3: Modified Team TRIMP Zones and Weighting (Stagno, Thatcher, and Van Someren, 2007, p. 632)*

<b>Zone</b>	<b>% Max HR</b>	<b>Weighting</b>
<b>1</b>	65-71	1.25
<b>2</b>	72-78	1.71
<b>3</b>	79-85	2.54
<b>4</b>	86-92	3.61
<b>5</b>	93-100	5.16

In addition to calculating team TRIMP using the predetermined zones and weights described above, Stagno's protocol was replicated for the athletes in this study to produce a new algorithm for team TRIMP in female hockey athletes, termed fTRIMP (Stagno, Thatcher and Van Someren, 2007). Specifically, the concept of five weighted heart rate zones was maintained, but the zones and weightings were altered based on the blood lactate curve produced after the female participants' submaximal fitness testing. Firstly, exercising heart rate was calculated for each participant at each of the five stages of the submaximal treadmill test by determining the average heart rate during the final minute of the stage. Heart rate reserve (HRR), also known as fractional elevation, was then calculated from exercising heart rate as follows.

*Equation 3.5: Heart Rate Reserve (Stagno, Thatcher and Van Someren, 2007)*

$$\text{Heart Rate Reserve (HRR)} = \frac{\text{Exercising HR} - \text{Resting HR}}{\text{Maximum HR} - \text{Resting HR}}$$

Next, HRR was plotted against blood lactate for each participant at each stage to produce a team scatterplot. An exponential line of best fit was calculated based on the scatterplot, and this team blood lactate curve was used to set the five heart rate zones and weighting, as performed by Stagno, Thatcher, and Van Someren (2007). Using the curve of best fit, heart rate was determined at blood lactate concentrations of  $2 \text{ mmol}\cdot\text{L}^{-1}$  and  $4 \text{ mmol}\cdot\text{L}^{-1}$ . These values were used as anchor values for the heart rate zones 2 and 4, and the remaining zones were fit around these anchors so that the zones were of approximately equal width. The weightings for each zone were then determined by taking the value of the blood lactate curve at the median heart rate for each zone.

The final algorithm used to measure TRIMP was the individualized TRIMP method, first described by Manzi et al. (2009). To calculate individualized TRIMP, HRR and blood lactate data points were calculated as described above. However, instead of combining all participants' data to produce a single curve, blood lactate scatterplots were produced separately for each individual. (Individualized TRIMP was not calculated for the one participant with trypanophobia, as it was not possible to determine her HRR versus blood lactate curve.) An exponential model was used to produce equations of the form  $y = ae^{bx}$  where  $a$  and  $b$  were set constants, distinct for each individual. Instead of using five heart rate zones, the weighting for each recorded heart rate value was calculated separately. Specifically, the weighting for each heart rate measurement was given by the exponential equation derived from an individual's blood lactate curve. This is summarized in the following equation in which  $a$  and  $b$  are the individualized constants described above, and  $e$  is the base of the natural logarithm.

*Equation 3.6: Individualized TRIMP Weightings (Manzi et al., 2009)*

$$\text{Weighted value} = \text{HRR} \times ae^{b \times \text{HRR}}$$

These weighted values were then summed for all recorded heart rate data points over the course of the session and divided by the number of heart rate data points measured per second. In summary, the Equation 3.3 was used to calculate individualized TRIMP. In this equation  $\text{HR}$  is the recorded heart rate,  $n$  is the number of heart rate readings recorded per minute,  $\text{HR}_{\text{rest}}$  is resting heart rate and  $\text{HR}_{\text{max}}$  is maximum heart rate, and  $a$  and  $b$  are constants determined by an individual's blood lactate curve.



*Equation 3.7: Individualized TRIMP*

$$iTRIMP = \frac{1}{n} \sum_{HR} \left( \frac{HR - HR_{rest}}{HR_{max} - HR_{rest}} \right) \times ae^{b \left( \frac{HR - HR_{rest}}{HR_{max} - HR_{rest}} \right)}$$

### 3.5.2 Demands of Hockey Competition and Training

In addition to TRIMP, several other training load measures were calculated for participants during competition and training. Specifically, total distance, distance in speed zones, workrate, minutes played, average heart rate, and effindex were measured. The six speed zones used were 1) 0-0.6, 2) 0.7-6.0, 3) 6.1-11.0, 4) 11.1-15.0, 5) 15.1-19, 6) >19.0 km·hr<sup>-1</sup> (Macutkiewicz and Sunderland, 2011; Abbott, 2016).

During competition, bench time was excluded, leaving only time on the pitch to be considered, as was suggested by White and MacFarlane for time-dependent measures (2013). During training, technical drills focused on skill acquisition were excluded due to their stationary nature, designed for learning and not intended to mirror match play. Thus, the training drills considered were various small-sided games in which reduced numbers played modified games on a small pitch, often to focus on a particular team concept. Time between drills (talking, water breaks, etc.) was phased out of the data in order to measure relative training volume, as described by Bompa (1999). Unphased data sets were also calculated and recorded for all sessions in order to determine cumulative loads.

### 3.5.3 Measurement of Fitness Outcomes

The relationships between various training load measures and fitness and fitness changes over the course of the season were also investigated to determine which measure, if any, best predicted fitness outcomes. Fitness changes were measured via the submaximal fitness test that participants completed at the beginning and end of the study, as submaximal parameters have been shown to be more sensitive to training-induced changes than maximal volume of oxygen consumption (VO<sub>2</sub> max) (Impellizzeri, Rampinini and Marcora, 2005). Specifically, as described by Manzi et al. (2009), heart rate and velocity were plotted against blood lactate. Blood lactate concentrations of 2 mmol·L<sup>-1</sup> and 4 mmol·L<sup>-1</sup> were taken as benchmarks for the lactate threshold (LT) and the onset of blood lactate accumulation (OBLA), respectively (Manzi *et al.*, 2009). By method of exponential interpolation, velocities at blood lactate concentrations of 2 mmol·L<sup>-1</sup> (v<sub>LT</sub>) and 4 mmol·L<sup>-1</sup> (v<sub>OBLA</sub>) were determined for each individual. Differences in these values at the beginning and end of the study

were used to assess fitness improvement or loss, with increased velocities indicating increased fitness, as was performed in previous training load studies (Akubat *et al.*, 2012; 2014; Malone and Collins, 2016; Manzi *et al.*, 2009; 2013). Lab-based fitness test scores were calculated by taking the mean of predicted velocity at blood lactate concentrations of 2 mmol·L<sup>-1</sup> and 4 mmol·L<sup>-1</sup>, thereby combining the two thresholds measured during testing. Specifically, fitness change was defined as percent change in lab-based fitness test scores from the start to the end of the study, where overall fitness was defined by both mean 30:15 scores and mean lab-based fitness test scores at the start and end of the study. All training load measures were compared to overall fitness as well as fitness changes. For this analysis, all unphased data over the entire study, including both trainings and competitions (with bench time and technical drills included), was incorporated into average weekly values for each training load variable to provide the most complete picture of each athlete's hockey training. The strength of the correlations between fitness and fitness changes and average weekly training loads were used to determine which training load measures best predict fitness outcomes.

#### 3.5.4 Effindex

Effindex was calculated during all sessions, and effindex scores were compared across halves in competition to provide information on how efficiency changed over the course of a match. To calculate effindex, ratios of distance measures were taken with heart rate measures, as described in research on football athletes (Torreno *et al.*, 2016; Arrones *et al.*, 2014; Akubat and Abt, 2011). Specifically, effindex<sup>1</sup> was defined to be *total distance: iTRIMP* and effindex<sup>2</sup> to be *meters per minute: average heart rate*.

#### 3.5.5 Statistical Analysis

Data are presented as means ± standard deviations. Training and competition training loads were compared using paired sample t-tests with Cohen's effect size statistic. Correlation analyses between training load measures, and between training load measures and fitness changes were performed using Pearson's product-moment coefficient. Statistical significance was set at p<0.01, to favor minimizing type 1 errors. Data were analyzed using SPSS for Windows (IBM SPSS, Version 22, Armonk, New York) and Microsoft Excel (Microsoft Corporation 2016, Version 1902, Redmond, Washington).

## Chapter 4: Results

### 4.1 Measuring Training Load in Female Hockey Athletes

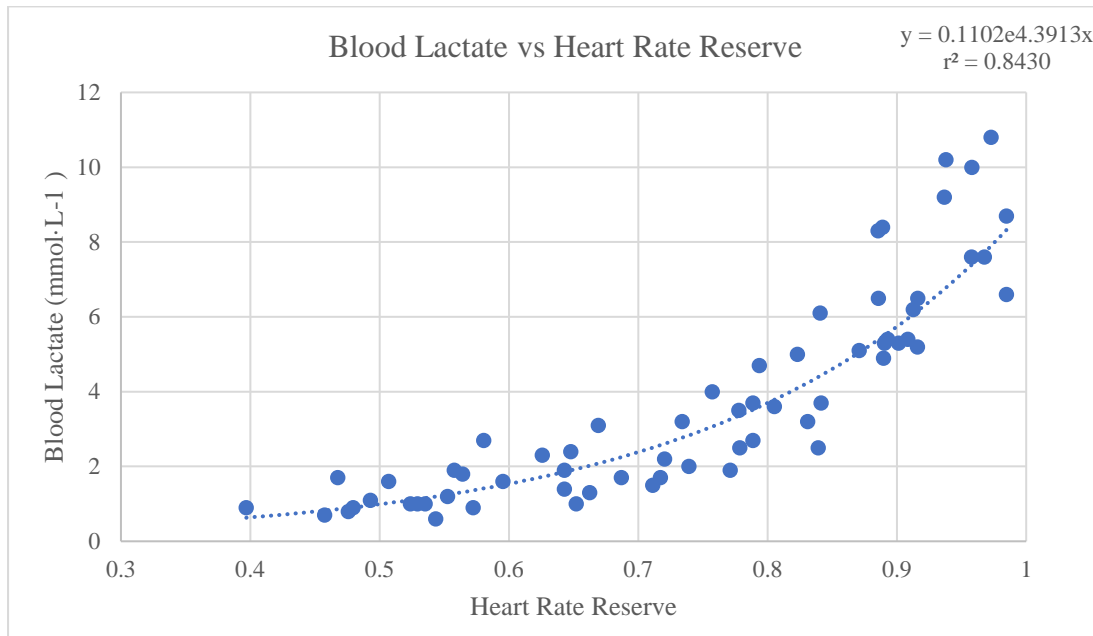


Figure 4.1: Blood Lactate versus Heart Rate Reserve

There was an exponential relationship between blood lactate and heart rate reserve (HRR), well modelled ( $r=0.918$ ) by the exponential curve  $y = 0.1102e^{4.3913x}$  (Figure 4.1).

Table 4.1: Stagno TRIMP & fTRIMP Algorithms (Stagno, Thatcher and Van Someren, 2007 p. 632)

Stagno's TRIMP	
%MaxHR	Weight
65-71	1.25
72-78	1.71
79-85	2.54
86-92	3.61
93-100	5.16

fTRIMP	
%MaxHR	Weight
59-66.9	0.91
67-74.9	1.49
75-82.9	2.44
83-90.9	3.99
91-100	6.74

The fTRIMP algorithm, based on this curve, had different weights and zone cutoffs than Stagno's TRIMP algorithm (Table 4.1).

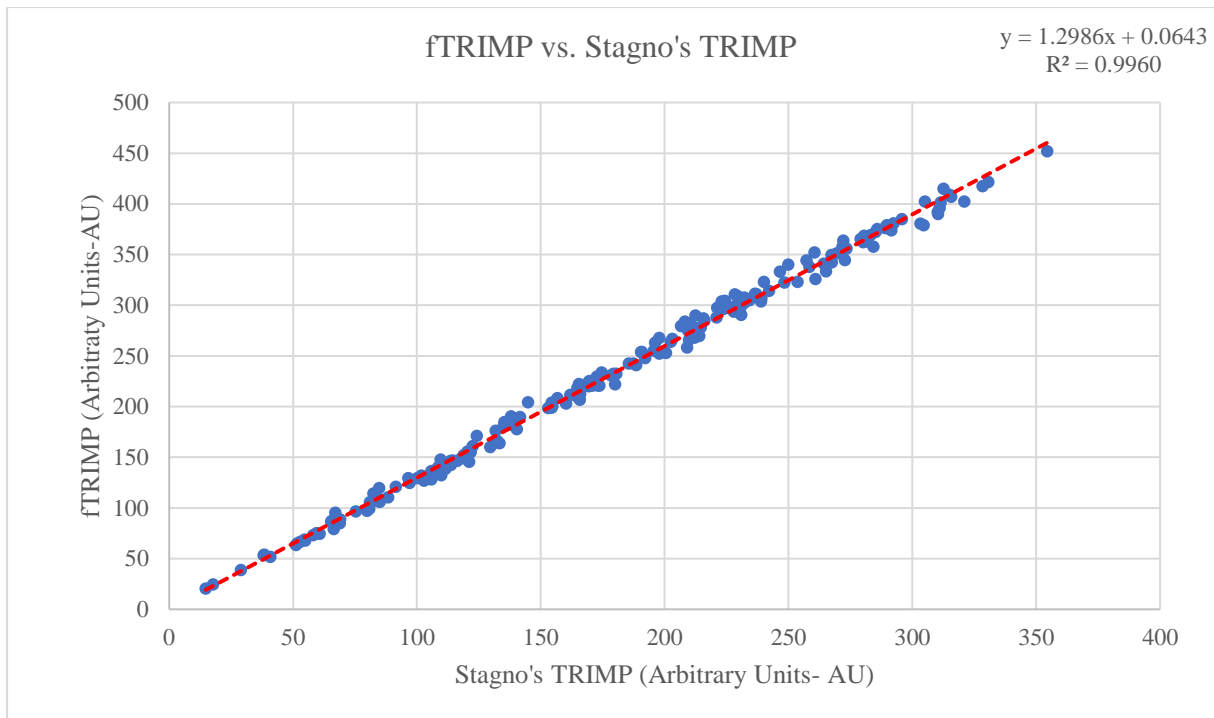


Figure 4.2: Relationship between Team TRIMP Algorithms

Despite these differences, fTRIMP scores were still extremely strongly correlated ( $r=0.998$ ) with Stagno's TRIMP scores across all unphased data (Figure 4.2).

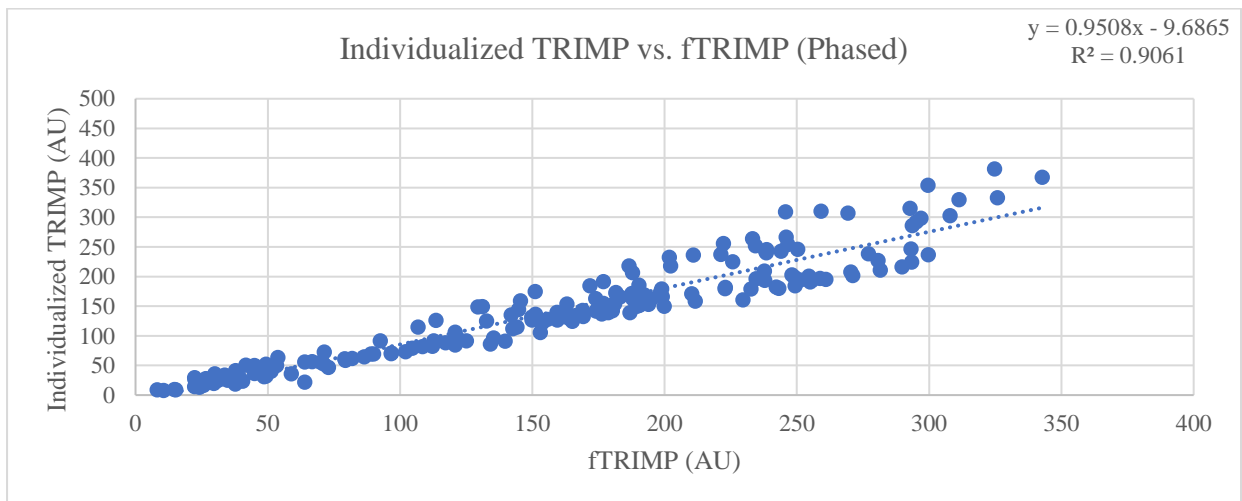


Figure 4.3: Individualized TRIMP vs. fTRIMP (Phased)

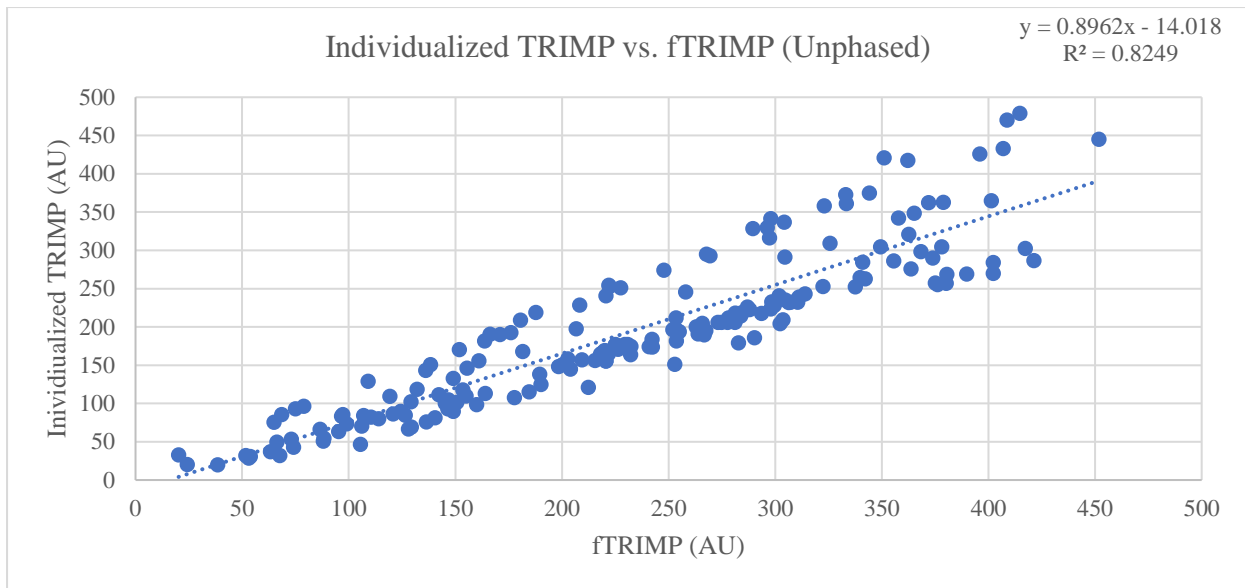


Figure 4.4: Individualized TRIMP vs. fTRIMP (Unphased)

There was also a strong relationship between fTRIMP and iTRIMP. When phased data, including only small-sided games in training and on the pitch in competition, were analyzed, this relationship was stronger (Figure 4.3) than when unphased data were analyzed (Figure 4.4).

Table 4.2: Correlation of Heart-Rate Based Training Load Measures

Correlation of Heart-Rate Based Training Load Measures				
	Stagno TRIMP	fTRIMP	iTRIMP	%MaxHR
Stagno TRIMP	1	0.998	0.906	0.926
fTRIMP	0.999*	1	0.908	0.921
iTRIMP	0.950*	0.952*	1	0.838
%MaxHR	0.523*	0.540*	0.538*	1

\*: Phased Data    No \*: Unphased Data

Average percentage of maximum heart rate (%MaxHR) was strongly correlated with TRIMP scores when unphased data were considered but only moderately correlated when phased data were considered (Table 4.2).

*Table 4.3: Correlation of sRPE to Other Training Load Measures*

<b>Correlation (r) of Session RPE to Other Training Load Measures</b>			
	Overall sRPE	fTRIMP	Total Distance
Overall sRPE	1	0.927	0.926
Respiratory sRPE	0.984	0.916	0.904
Lower body sRPE	0.958	0.884	0.890
Upper Body sRPE	0.573	0.527	0.668

Overall session RPE was very strongly correlated with fTRIMP ( $r=0.927$ ) and total distance ( $r=0.926$ ). Respiratory and lower body differential sRPE were also strongly correlated with overall sRPE (respiratory:  $r=0.984$ ; lower body:  $r=0.958$ ), fTRIMP (respiratory:  $r=0.916$ ; lower body:  $r=0.884$ ), and total distance (respiratory:  $r=0.904$ ; lower body:  $r=0.890$ ), while upper body sRPE was only moderately correlated with other measures of training load (Table 4.3). All sRPE scores were calculated for phased data, as only active time was counted towards athletes' minute totals.

*Table 4.4: Correlation of Internal and External Training Load Measures*

<b>Correlation of Internal and External Training Load Measures</b>				
	Stagno TRIMP	fTRIMP	iTRIMP	%MaxHR
Total Distance	0.957	0.949	0.882	0.430
Workrate	0.286	0.300	0.283	0.689
Zone 1	0.475	0.469	0.379	0.062
Zone 2	0.857	0.841	0.804	0.184
Zone 3	0.917	0.910	0.901	0.425
Zone 4	0.898	0.898	0.823	0.556
Zone 5	0.824	0.821	0.707	0.479
Zone 6	0.549	0.542	0.379	0.260

The correlations of internal and external training load measures were considered over all phased data (Table 4.4). TRIMP scores were most strongly correlated with total distance followed by distance covered in zones 3 and 4. Average percentage of maximum heart rate was most strongly correlated with workrate ( $r=0.689$ ) but only weakly and moderately

correlated with other measures of external training load. Distances covered in zones 5 and 6 were only moderately correlated with team TRIMP scores.

*Table 4.5: Fitness Test Scores*

<b>Fitness Test Scores (Mean <math>\pm</math> SD)</b>		
	Pre-test	Post-test
Lab-based (km $\cdot$ hr <sup>-1</sup> )	10.67 $\pm$ 1.10	11.31 $\pm$ 0.92
30:15	19.50 $\pm$ 0.63	19.45 $\pm$ 0.57

Lab-based fitness test scores were given by mean predicted velocity at blood lactate concentrations of 2 and 4 mmol $\cdot$ L<sup>-1</sup> during the submaximal treadmill test. There was a notable improvement in lab-based fitness test scores from pre-testing to post-testing and a slight decrease in standard deviation (Table 4.5). There was no notable change in average 30:15 scores.

*Table 4.6: Correlation of Training Load Measures to Fitness*

<b>Correlation of Training Load Measures to Fitness</b>			
	Lab-Based Fitness Score	Average 30:15 Scores	Percent Fitness Change
Respiratory sRPE	-0.033	0.349	-0.103
Upper Body sRPE	-0.014	-0.058	0.030
Lower Body sRPE	0.215	0.464	-0.017
Overall sRPE	0.109	0.469	0.160
Stagno TRIMP	-0.732	-0.164	0.134
fTRIMP	-0.740	-0.162	0.150
iTRIMP	-0.662	-0.190	0.597
%MaxHR	-0.832	-0.310	0.249
Total Distance	0.358	0.431	-0.441
Workrate	0.222	-0.036	0.079
Zone 1	-0.141	0.271	-0.026
Zone 2	0.153	0.000	-0.509
Zone 3	-0.020	-0.095	0.239

Zone 4	0.062	0.138	-0.155
Zone 5	0.639	0.801	-0.622
Zone 6	0.842	0.881	-0.663
Effindex <sup>1</sup>	0.769	0.305	-0.477

Stagno TRIMP, fTRIMP, iTRIMP, %MaxHR, distance covered in zones 5 and 6, and effindex<sup>1</sup> were moderately correlated with lab-based fitness test scores (Table 4.6). The moderate relationships between lab-based fitness test scores and external training load were positive, while the relationships with internal training load were negative. Average 30:15 scores were strongly correlated with distance covered in zones 5 ( $r=0.801$ ) and 6 ( $r=0.881$ ). Percent change in fitness was calculated from mean predicted blood lactate concentrations at 2 and 4 mmol·L<sup>-1</sup> measured before and after the study. Individualized TRIMP was the only training load measure moderately positively correlated with percent fitness change ( $r=0.597$ ). Distance covered in zones 5 ( $r=-0.622$ ) and 6 ( $r=-0.663$ ) were moderately negatively correlated with percent fitness change. Percent fitness change was also negatively correlated with fitness scores measured at the start of the study ( $r=-0.655$ ), indicating that fitter athletes improved their fitness less over the course of the study.

#### 4.2 Physical and Physiological Demands of British University Hockey

*Table 4.7: Match Descriptives*

<b>Match Descriptives</b>			
	Mean ± SD	Minimum	Maximum
Minutes	46.95 ± 10.20	25.57	74.90
Respiratory sRPE	301 ± 93	102	511
Upper Body sRPE	140 ± 73	0	370
Lower Body sRPE	293 ± 92	100	517
Overall sRPE	300 ± 87	102	501
Stagno TRIMP	172 ± 36	99	268
fTRIMP	223 ± 48	121	343
Individualized TRIMP	199 ± 62	84	381
%MaxHR	0.883 ± 0.031	.792	.944



Total Distance (m)	5419 ± 886	3177	7676
Workrate (m·min <sup>-1</sup> )	117.1 ± 10.6	89.2	142.1
Zone 1 (m)	54 ± 44	1	229
Zone 2 (m)	1415 ± 415	649	2435
Zone 3 (m)	1772 ± 402	910	3002
Zone 4 (m)	1306 ± 218	814	1774
Zone 5 (m)	642 ± 154	299	1098
Zone 6 (m)	228 ± 134	59	780
Effindex <sup>1</sup>	29.0 ± 7.2	17.3	55.5
Effindex <sup>2</sup>	1.33 ± 1.07	1.05	1.61

Athletes in this study covered, on average, 5419m during competition and recorded an average fTRIMP score of 223 (AU) (Table 4.7). Physical and physiological demands during competition varied largely, as evidenced by the large range and standard deviation values. For example, distance covered in zone 6 ranged from 59m to 780m and %MaxHR ranged from 79.2% to 94.4%. Additionally, average effindex<sup>1</sup> was considered separately decreased from 1.35 in the first half to 1.31 in the second half. All match data were phased to only include time on the pitch.

*Table 4.8: Average Weekly Load (Phased)*

<b>Average Weekly Load (Phased)</b>	
	Mean ± SD
Minutes	134.46 ± 18.37
Respiratory sRPE	818 ± 154
Upper Body sRPE	400 ± 158
Lower Body sRPE	797 ± 149
Overall sRPE	813 ± 143
Stagno TRIMP	463 ± 61
fTRIMP	597 ± 80
Individualized TRIMP	523 ± 98
%MaxHR	0.867 ± 0.022
Total Distance (m)	14888 ± 1590
Workrate (m·min <sup>-1</sup> )	113.1 ± 7.0

Zone 1 (m)	151 ± 70
Zone 2 (m)	4134 ± 731
Zone 3 (m)	4892 ± 685
Zone 4 (m)	3430 ± 407
Zone 5 (m)	1669 ± 253
Zone 6 (m)	612 ± 219
Effindex <sup>1</sup>	31.7 ± 4.8
Effindex <sup>2</sup>	130.4 ± 7.0

In an average week, athletes covered 14.8 km during active time in training and matches, with a mean %MaxHR of 86.7% (Table 4.8). Of the 14.8km, only 612m were covered at speeds of 19 km·hr<sup>-1</sup> or higher, and average weekly cumulative fTRIMP was 597 (AU) (Table 4.8).

*Table 4.9: Average Weekly Load (Unphased)*

<b>Average Weekly Load (Unphased)</b>	
	Mean ± SD
Minutes	396.63 ± 15.85
Stagno TRIMP	695 ± 86
fTRIMP	902 ± 110
Individualized TRIMP	734 ± 130
Total Distance (m)	23441 ± 1794
Zone 1 (m)	678 ± 223
Zone 2 (m)	9039 ± 996
Zone 3 (m)	6911 ± 749
Zone 4 (m)	4171 ± 422
Zone 5 (m)	1924 ± 298
Zone 6 (m)	715 ± 2389

When unphased data were considered for cumulative training load measures, total distance increased to 23.4 km, with 714m above 19 km·hr<sup>-1</sup>, and weekly average fTRIMP increased to 902 (AU) (Table 4.9).

Table 4.10: Range in Individual Average Weekly Load

Range in Individual Average Weekly Load		
	Minimum	Maximum
Minutes	390.84	400.85
Respiratory sRPE*	573.6766	1008.274
Upper Body sRPE*	129.8001	701.6914
Lower Body sRPE*	560.7156	1015.598
Overall sRPE*	601.0925	977.3004
Stagno TRIMP	472.8939	809.4588
fTRIMP	614.415	1057.809
Individualized TRIMP	447.7877	1104.583
%MaxHR*	0.815375	0.905479
Total Distance (m)	21609.95	24978.32
Workrate (m·min <sup>-1</sup> )*	96.23863	119.8507
Zone 1 (m)	71.73333	1109.617
Zone 2 (m)	7293.5	9908.55
Zone 3 (m)	5766.086	8118.131
Zone 4 (m)	3444.633	4723.667
Zone 5 (m)	1462.15	2361.705
Zone 6 (m)	456.1143	1209.448
Effindex <sup>1</sup> *	20.58188	44.79038
Effindex <sup>2</sup> *	112.5933	142.0711

\*: Phased Data    No \*: Unphased Data

Average weekly load greatly varied by participant, as evidenced by the large range in individual average weekly training loads (Table 4.10).

Table 4.11: Competition vs. Training Data

Competition vs. Training Data (Phased)				
	Competition	Training	Cohens D	p-value
Minutes	46.95	21.15	2.31	0
Respiratory sRPE	301	118	2.04	0

Upper Body sRPE	140	66	0.86	0.001
Lower Body sRPE	293	116	2.05	0
Overall sRPE	300	118	2.14	0
Stagno TRIMP	172	62	2.92	0
fTRIMP	223	79	2.92	0
Individualized TRIMP	199	66	2.40	0
%MaxHR	0.883	0.823	1.11	0
Total Distance (m)	5419	2122	3.13	0
Workrate (m·min <sup>-1</sup> )	117.1	102.8	0.86	0
Zone 1 (m)	54	22	0.89	0.005
Zone 2 (m)	1415	679	1.79	0
Zone 3 (m)	1772	705	2.63	0
Zone 4 (m)	1306	429	3.44	0
Zone 5 (m)	642	204	2.78	0
Zone 6 (m)	229	83	1.22	0.002

The physical and physiological demands of training were significantly different than the demands of competition for all training load measures (Table 4.11). Based on a paired sample t-test,  $p < 0.01$  and effect sizes, given by Cohen's D, were very large for all measures.

*Table 4.12: Competition TRIMP Scores Based on Phasing*

<b>Competition TRIMP Scores based on Phasing</b>			
	Time-on-pitch	Entire game (including bench time)	Entire session (including bench time and warmup)
Stagno TRIMP	172 ± 36	198 ± 41	237 ± 49
fTRIMP	223 ± 48	261 ± 53	309 ± 63
iTRIMP	199 ± 63	222 ± 68	256 ± 79

In competition, phasing made a notable difference in TRIMP scores (Table 4.12). As TRIMP is cumulative, entire session scores (including time on bench and warmup) were greater than entire game scores (including time on the bench), both of which were greater than scores from just time on the pitch.

## Chapter 5: Discussion – Measuring Training Load in Female Hockey Athletes

### 5.1 Developing a New Female Team TRIMP Algorithm

This study is the first to modify Stagno's team TRIMP algorithm for female athletes and, therefore, provides novel insight on the importance of using gender-specific team TRIMP algorithms. Stagno's algorithm summarizes heart rate over the course of a hockey training session or match; however, as the study was performed only on men, there is no evidence to support the use of Stagno's algorithm on female athletes (Stagno, Thatcher and Van Someren, 2007). This study found that replicating Stagno's protocol on female hockey athletes resulted in a new, distinct algorithm for team TRIMP. Although the same procedure was followed, using exponential interpolation to assess the relationship between blood lactate and HRR and then fitting zones around the anchors of 1.5 and 4 mmol·L<sup>-1</sup>, the new algorithm differed from the original in both the zone cutoffs and weights (Table 4.1) (Stagno, Thatcher and Van Someren, 2007).

The main difference between the male athletes in Stagno's study and the female athletes in the current study was the rate of increase of the blood lactate concentration versus HRR curve (Stagno, Thatcher and Van Someren, 2007). Specifically, when blood lactate concentration was plotted against HRR, as measured during a submaximal lactate threshold treadmill test, the relationship was best described by  $y = 0.1102e^{4.3913x}$ , as demonstrated in Figure 4.1. Furthermore, the strength of the correlation was very strong ( $r = 0.918$ ), indicating that the exponential curve used was a very good fit for the data. As a comparison, for the eight male athletes in the Stagno study, blood lactate versus HRR was best modeled by the curve  $y = 0.1225e^{3.9434x}$  (Stagno, Thatcher and Van Someren, 2007). Although the intercepts of these models are very similar, the difference in the exponential term indicates that as HRR increases, blood lactate increases at a higher rate in female athletes than in male athletes. Thus, as HRR approaches one, the blood lactate corresponding to a set HRR will be much higher for the females in this study than was reported previously for male athletes (Stagno, Thatcher and Van Someren, 2007). For example, at a HRR of 0.9, the predicted blood lactate concentration is 4.3 mmol·L<sup>-1</sup> for male athletes and 5.7 mmol·L<sup>-1</sup> for female athletes, a difference of 33%. When working at maximum heart rate, the predicted concentrations increase to 6.3 mmol·L<sup>-1</sup> for males and 8.9 mmol·L<sup>-1</sup> for females, a difference of 41%. These results suggest that the physiological demands of working at higher values of HRR are greater in female athletes than in male athletes.

To date, no study has directly investigated sex differences in the blood lactate versus HRR curve. As with the Stagno study, the majority of studies investigating the relationship between heart rate and blood lactate have been performed on male athletes (Akubat *et al.*, 2012; Akubat and Abt, 2011; Banister, 1991; Malone and Collins, 2016; Manzi *et al.*, 2009; Manzi *et al.*, 2013; Stagno, Thatcher and Van Someren, 2007). Studies that have considered the relationship between sex and blood lactate have focused on peak blood lactate concentration and lactate removal and have found no significant differences in these measures between sexes (Froberg and Pedersen, 1984; Lehmann, Berg and Keul, 1986; Zhang and Ji, 2016). However, as the treadmill test used to calculate team TRIMP is submaximal, athletes are not likely to have reached peak blood lactate concentrations. Although the relationship between heart rate and blood lactate concentration was not considered, an early study measuring sex differences in catecholamines during graded treadmill running examined sex differences in blood lactate levels (Lehmann, Berg and Keul, 1986). As part of the study, 15 trained adults, 9 females and 6 males, completed a treadmill test commencing at 6 km·hr<sup>-1</sup> and consisting of stages of 3 minutes of running followed by 30 seconds of recovery and increasing by 2 km·hr<sup>-1</sup> each stage until exhaustion (Lehmann, Berg and Keul, 1986). The results showed that at identical running intensities, female participants had higher blood lactate concentrations than males, with the difference increasing as running speed increased (Lehmann, Berg and Keul, 1986). While it is not possible to know if there was a corresponding increase in heart rate, these findings are in alignment with the results of this study, indicating that blood lactate levels increase more quickly in females than in males as HRR rises during submaximal exercise (Lehmann, Berg and Keul, 1986). Similarly, a 2014 study on sex differences in lactate threshold among football players reported that velocities at blood lactate concentrations of 4 mmol·L<sup>-1</sup> were significantly lower ( $p=0.003$ ) in females than in males, while at 2 mmol·L<sup>-1</sup>, the velocities for females were lower, but not significantly ( $p=0.138$ ) (Baumgart, Hoppe and Freiwald, 2014). Although the relationship with heart rate was not considered, these findings also support the results of this study, suggesting that as intensity rises, blood lactate levels increase more rapidly in females than in males (Baumgart, Hoppe and Freiwald, 2014).

As a result of the different blood lactate curves for males and females, both the zone cutoffs and weights varied between Stango's TRIMP algorithm and the fTRIMP algorithm. The elevated rate of increase of blood lactate versus HRR in female athletes led to higher weightings for the top zones and lower weightings for the lower zones in the fTRIMP algorithm. Specifically, in the new algorithm the weighting for the top zone was 21.8%

higher than in the Stagno algorithm and the weighting for the lowest zone was 27.2% lower than in the Stagno algorithm. As described by Stagno et al., to determine zone widths and cutoffs, zones 2 and 4 were anchored around blood lactate concentrations of  $1.5 \text{ mmol}\cdot\text{L}^{-1}$  and  $4 \text{ mmol}\cdot\text{L}^{-1}$ , respectively, and the remaining zones were fit around these two, with approximately equal widths (Stagno, Thatcher and Van Someren, 2007). Since the female athletes in this study reached blood lactate concentrations of  $1.5 \text{ mmol}\cdot\text{L}^{-1}$  and  $4 \text{ mmol}\cdot\text{L}^{-1}$  at lower values of HRR than the males in the Stagno study, the cutoffs for the zones were lower. As all HRR values up to 1.0 still needed to be included in the algorithm, the lower cutoffs led to increased zone widths, especially for the top zone. Overall, as can be seen in Table 4.1, the zone cutoffs, widths, and weights are notably different in the fTRIMP algorithm, compared to Stagno's TRIMP algorithm.

The differences between these two algorithms suggest that using the Stango TRIMP algorithm for the female hockey athletes in the current study will result in an underestimation of training load. Specifically, work near maximum heart rate will be underweighted compared to its physiological impact, in terms of blood lactate concentration. Additionally, the findings of this study suggest that if the Stagno algorithm is used for female athletes, work at 59-64.9% of maximum heart rate will not be accounted for, even though the evidence suggests that blood lactate accumulates at lower heart rate values in females than in males. Despite the very notable differences in the two algorithms, fTRIMP and Stagno TRIMP scores, considered across all data in the study, were still extremely strongly correlated ( $r=0.998$ ), as demonstrated in Figure 4.2. A correlation of moderate strength is to be expected as the two team TRIMP measures were based on the exact same heart rate data and used a similar method of five weighted zones to process that data. However, the correlation between the two TRIMP algorithms is extremely strong ( $r=0.998$ ), not just moderate, and, as the models are both exponential, the linearity of this correlation is not intuitive. Since the data are correlated, not equivalent, using Stagno's algorithm on female athletes will consistently and systematically underestimate training load. As the units of TRIMP are arbitrary, this underestimation is irrelevant in the case where only one sex is being considered since the extreme linearity of the correlation means that the underestimation will be consistent. However, when both sexes are analyzed or when team TRIMP is being used to set thresholds for training loads, the underestimation will result in discrepancies between male and female data.

The linearity of the relationship between Stagno's TRIMP and fTRIMP allows for a simple resolution of the inconsistencies between male and female team TRIMP data.

Specifically, the extreme strength of the linear correlation ( $r=0.998$ ) indicates that instead of using two distinct algorithms to analyze male and female heart rate data, a single algorithm can be used, if followed by a simple linear transformation based on gender. In practice, this result greatly simplifies matters for analysts working with both male and female athletes, as existing software programs, such as *Catapult Sprint*, often only allow for one team TRIMP algorithm to be inputted at any given time. Thus, instead of needing to analyze heart rate data for male and female athletes separately using distinct algorithms, all data can be analyzed together, using the same algorithm, if a transformation is performed to correct for the differences in male and female data. The relationship between the male and female algorithms is further simplified by the fact that there is insufficient evidence to suggest that the constant in the equation is non-zero. Specifically, the value of the constant is 0.064 and the standard error is 1.141, so there is not adequate evidence to conclude that the value is significant. Additionally, TRIMP is usually rounded to the closest integer value, so adding 0.064 is irrelevant. Ignoring the constant, the transformation simplifies to a multiplicative factor of 1.299 (standard error 0.006). Therefore, in order to adjust for sex differences in the physiological response to exercise, female team TRIMP scores calculated using the Stagno algorithm should be multiplied by 1.3. Alternatively, if scores are not adjusted, training load targets for male athletes should be reduced by a factor 1.3 when applied to females. For example, if the target load for males is 130, the corresponding target load for females should be 100. Regardless of what method of adjustment is used, the results of this study demonstrate the importance of not simply applying male team TRIMP protocols to female athletes, and, with a multiplicative factor of 1.3, provide a simple method for doing so.

## 5.2 Correlations of Training Load Measures

### 5.2.1 Relationship between Heart-Rate Measures

In addition to developing a new method of measuring team TRIMP in female athletes, this study also investigated iTRIMP and average percentage of maximum heart rate (%MaxHR) as training load measures. Specifically, iTRIMP was strongly correlated with both Stagno TRIMP ( $r=0.906$ ) and fTRIMP ( $r=0.908$ ) across all unphased data. Although strong, these correlations were not as large as the correlation between Stagno TRIMP and fTRIMP ( $r=0.998$ ). This result suggests that there was more than a simple linear transformation of the data occurring when the iTRIMP algorithm was used instead of the



fTRIMP algorithm. In fact, examining the relationship between iTRIMP and fTRIMP, as shown in Figure 4.4, demonstrates that for larger fTRIMP scores, iTRIMP values diverged farther from the linear model. Furthermore, most of the values cluster just below the line of best fit indicating that in most cases there was a very strong linear relationship between iTRIMP and fTRIMP; however, the data points that fall above the line of best fit are farther spread, generally in a linear fashion but with a slightly larger slope. Overall, the spread around the linear model suggests that using individualized TRIMP scores provides different information on training load than that which can be obtained from team TRIMP algorithms. Since iTRIMP algorithms are individualized, it has been suggested that iTRIMP data will be more accurate, and, as such, should be used instead of team TRIMP algorithms (Manzi *et al.*, 2009; Malone and Collins, 2016).

When data are phased and just active time is considered, the strength of the correlation between iTRIMP and fTRIMP increases ( $r=0.952$ ), as shown in Figure 4.3. In this case, the data are much more closely and consistently clustered around the regression line, demonstrating that very little distinct information is obtained from iTRIMP compared to fTRIMP. Therefore, although the data obtained from the iTRIMP algorithm may be considered to be more accurate since it is individualized, the strength of the correlation shows that scores obtained using the iTRIMP algorithm will be very close to a simple linear transformation of fTRIMP scores. As the units of TRIMP are arbitrary, the linearity of the relationship between fTRIMP and iTRIMP means that as long as one algorithm is consistently used, the training load information obtained from monitoring active training will be very similar, albeit on slightly different linear scales.

As iTRIMP and fTRIMP are so closely related for active data, the question that then arises is, from a practical standpoint, whether using iTRIMP is worth the additional effort required. Calculating iTRIMP requires lab-based fitness testing, including blood lactate measurement, on all athletes to determine their HRR versus blood lactate curve. This testing should be repeated regularly, perhaps once per season, to account for physiological changes that may occur and to ensure that the algorithms are still accurate for each individual. On the other hand, using a team TRIMP algorithm requires no testing, as zone cutoffs and weights are predetermined by either the Stagno algorithm for male athletes or the fTRIMP algorithm for female athletes. Since the resources required for lab-based testing will be unavailable to the vast majority of hockey teams, team TRIMP algorithms provide a more accessible method of monitoring athletes. Furthermore, if only active time is considered, the results of this study suggest that very similar training load scores can be obtained by completely

forgoing individualized testing and simply using the team TRIMP algorithms. However, as the correlation between iTRIMP and fTRIMP is strong, but not perfect, there will still be some different information provided by iTRIMP versus fTRIMP training load scores, so teams with the resources, such as top international programs, may benefit from using iTRIMP if they wish to have the most accurate individualized monitoring.

The results of this study demonstrate that %MaxHR is also an accurate method of monitoring internal training load in hockey training and competition, as long as complete, unphased data sets are analyzed. Considering only phased data (active time during training or time on the pitch during competition), the results of this study suggest that %MaxHR is not an accurate method of monitoring internal training load since there is only a weak moderate correlation with fTRIMP ( $r=0.540$ ). However, when the phasing is removed and sessions are considered in their entirety, the strength of the correlation between %MaxHR and fTRIMP drastically increases to  $r=0.921$ . This result is very interesting as one might expect that considering time between drills in training and off the pitch during competition would skew %MaxHR scores. In fact, the majority of studies measuring %MaxHR have phased data to only include time on the pitch during competition (Lythe, 2008; Macutkiewicz and Sunderland, 2011; Boran, 2012; Sell and Ledesma, 2016; Vescovi, 2016; McGuinness *et al.*, 2017). Furthermore, it has been suggested that only considering average heart rate oversimplifies the varied and intermittent demands of team sports such as hockey (Stagno, Thatcher and Van Someren, 2007). However, the strong correlation between %MaxHR and fTRIMP across all unphased data in this study ( $r=0.952$ ) clearly suggests that %MaxHR is a valid method of measuring internal training load and will provide very similar information to team TRIMP scores.

From a practical perspective, the simplicity of %MaxHR increases its potential as a training load measure. No algorithms need to be used, and even the least sophisticated heart rate monitoring equipment will include average heart rate in the output. As heart rate monitors are becoming increasingly more popular and less cost-prohibitive, it is not unreasonable for hockey clubs to have a set of heart rate monitors for athletes to wear. Furthermore, since no data analysis is needed, %MaxHR monitoring could be performed by coaches rather than sports scientists. Thus, using %MaxHR as a training load measure greatly simplifies the monitoring process, making it more accessible to a large range of hockey clubs. In addition, the fact that unphased %MaxHR data should be used to ensure a strong relationship with team TRIMP is fortuitous, as phasing data is one of the most time-consuming aspects of data analysis. Also, less sophisticated (and oftentimes less expensive)

heart-rate monitored equipment will not allow for data phasing and will only include whole session reports in the output. From a scientific perspective, the need for unphased data is also beneficial, as it is preferable to measure internal load over entire sessions to ensure that the full physiological load is recorded. Athletes still have elevated heart rates as they recover either in-between training drills or off the pitch during competition, so using only phased data can skew training load scores. Therefore, %MaxHR is a very useful method for monitoring internal training load both scientifically and practically.

Overall, the results of this study indicate that there are many difference options for monitoring internal training load using heart-rate based measures in female hockey athletes. Previous studies have suggested that iTRIMP is the gold standard for measuring internal training load, as it is fully individualized based on each athlete's physiological response to exercise (Manzi *et al.*, 2009; Malone and Collins, 2016). Therefore, for teams that have the resources and interest in having the most accurate monitoring system for each athlete, iTRIMP can provide the detailed internal training load information desired. However, in the vast majority of cases, teams will not have the resources required for individual athlete lab-based testing. Thus, team TRIMP algorithms are preferable because the algorithms are preestablished and no lab-based testing is required. When data are phased to only include active data, there is a very strong correlation between iTRIMP and fTRIMP scores ( $r=0.952$ ), and, as the multiplicative factor of 1.3 between fTRIMP and Stagno's TRIMP has been established, it is possible to easily compare male and female team TRIMP data. Therefore, for teams that have the resources to calculate team TRIMP but not iTRIMP, the results of this study indicate that, if active data are used, little information is lost by using team TRIMP instead of iTRIMP. Finally, if calculating team TRIMP is not possible, %MaxHR can be used to monitor internal training load. Specifically, when unphased data are analyzed, %MaxHR is strongly linearly correlated with fTRIMP ( $r=0.921$ ), suggesting that %MaxHR can be used to provide accurate internal training load information without the complication of TRIMP algorithms. Therefore, depending on the resources available and level of accuracy required, teams can choose between iTRIMP, team TRIMP, or %MaxHR as valid methods of monitoring internal training load.

### 5.2.2 Validity of Session Rating of Perceived Exertion

This study was the first to measure sRPE in adult hockey, and the results indicate that sRPE is a valid method of measuring training load in female hockey training and competition. As sRPE is a perceptual measure, it has several practical advantages over other

methods of monitoring training load. No tracking devices or analytical support is required, and the only equipment needed is a stopwatch to track time. Instead of performing complicated analyses on massive datasets, a simple multiplication of RPE by time is all that is required to calculate sRPE scores. As RPE is a fully perceptual measure, questions have been raised as to the accuracy of the training load information obtained (Kolkhorst, Mittelstadt and Dolgener, 1996; Travlos and Marisi, 1996; Zeni, Hoffman and Clifford, 1996; Chen, Fan and Moe, 2002; Faulkner and Eston, 2007). However, in terms of sRPE in team sports, moderate to strong correlations have been found between sRPE and TRIMP in football ( $r=0.70$ ), Australian football ( $r=0.83$ ), and futsal ( $r=0.70$ ) (Impellizzeri *et al.*, 2004; Scott *et al.*, 2013b; Wilke *et al.*, 2016). Furthermore, sRPE was also shown to be moderately correlated with total distance ( $r=0.78$ ) in Australian football (Scott *et al.*, 2013b).

In terms of hockey training and competition, the results of this study indicate that overall sRPE is very strongly correlated with both team TRIMP and total distance. Specifically, across active data measured in all sessions, there was a very strong correlation between overall sRPE and fTRIMP ( $r=0.927$ ) and total distance ( $r=0.926$ ). Since these correlation coefficients are notably higher than what has been previously reported in other team-sport populations, this study is the first to show a very strong correlation between sRPE and internal and external training load measures in team sports (Impellizzeri *et al.*, 2004; Scott *et al.*, 2013b; Wilke *et al.*, 2016). These results provide strong evidence in support of sRPE as a valid method of measuring internal and external training load in female hockey training and competition. From a practical perspective, this result is very beneficial because, as mentioned above, sRPE scores are much easier to collect and calculate than other training load measures. In fact, as only a stopwatch is required, it is reasonable to assume that all hockey teams have the resources to collect individual sRPE scores if they chose to do so. Since the results of this study demonstrate that sRPE is a valid method of monitoring internal and external training load, the accessibility of sRPE means that all hockey teams have the ability to individually monitor their athletes.

In addition to overall sRPE, differential sRPE scores for respiratory, lower body, and upper body exertion were also measured as part of this study. Respiratory sRPE was extremely strongly correlated with overall sRPE ( $r=0.984$ ), indicating that respiratory fatigue greatly contributes to and is an accurate measure of overall exertion in hockey training and competition. Similarly, the very strong correlation between lower body sRPE and overall sRPE ( $r=0.958$ ) suggests that lower body exertion is also indicative of overall exertion. On the other hand, the much weaker correlation between upper body sRPE and overall sRPE

( $r=0.573$ ) shows that upper body exertion does not largely relate to overall exertion. This lower correlation is likely due to the fact that hockey primarily consists of sprinting, running, and walking which are far more taxing on the respiratory system and lower body than on the upper body.

As the relationships between overall sRPE and TRIMP and total distance were considered, the question naturally follows if respiratory sRPE and lower body sRPE are more closely related to other measures of internal and external training load than overall sRPE. One might hypothesize that, due to the nature of the exertion, respiratory sRPE would be more strongly correlated with TRIMP than overall sRPE and lower body sRPE would be more strongly correlated with total distance than overall sRPE. However, this is not the case, as overall exertion is better correlated with both TRIMP ( $r=0.927$ ) and total distance ( $r=0.926$ ) than either respiratory sRPE (TRIMP:  $r=0.916$ ; total distance:  $r=0.904$ ) or lower body sRPE (TRIMP:  $r=0.884$ ; total distance:  $r=0.890$ ). Therefore, these results suggest that overall sRPE is more effective than differential sRPE for monitoring internal and external training load.

As sRPE is a perceptual measure that can be easily influenced by how data are collected, it is important to consider exactly how sRPE scores were calculated in this study to ensure that teams using sRPE scores can accurately replicate important elements of the procedure. Firstly, as RPE scores are multiplied by time to produce sRPE scores, it is crucial that time is accurately measured. During this study, only active time either on the pitch during competition or in small-sided games during training was counted in athletes' minute totals for a session. Therefore, determining time is more complicated than measuring the entire length of a training session or competition. In practice, this can make calculating sRPE somewhat complicated, as it may be difficult to accurately monitor time for each athlete without the aid of GPS data sets, which allow analysts to retroactively determine exactly when players were active. However, during competition, team managers or technical directors often keep track of substitutions and the exact number of minutes played by each athlete. Additionally, during training, if coaches make precise plans regarding the length of small-sided game segments and follow those plans strictly without allowing teams to make substitutions, it is possible to easily determine the number of minutes that athletes were active during training. In addition to accurate timing, it is also important to note that overall RPE scores collected during this study were obtained as part of a questionnaire including respiratory, lower body, and upper body differential RPE. Without future research, it is impossible to determine if asking athletes to consider and report differential RPE scores prior

to an overall score influenced overall scores. Therefore, including differential scores in RPE questionnaires would be recommended, even if the overall score is the only one considered for analysis. Finally, RPE scores should be collected individually and athletes should be instructed not to discuss their scores with other athletes to reduce the influence of peer pressure.

Although, as previously discussed, there are many benefits of using sRPE as a measure of internal and external training load, it is also important to consider the limitations of sRPE. During this study, athletes' RPE scores were provided directly to the researcher, not to the coaching staff. Therefore, athletes knew that there would be no repercussions for their RPE scores and that coaches would not be able to use their RPE scores to judge their level of exertion or to determine the intensity of future sessions. As soon as RPE scores are provided to coaches and used to monitor training load, athletes may, subconsciously or not, change their behavior and reporting as a result of being monitored, an example of the Hawthorne effect (Buckworth, 2002). For instance, athletes may want to appear as if they are working hard and fully exerting themselves, particularly in competition settings, and, as a result, may inflate RPE scores. Additionally, if sRPE is used to monitor overall training load, athletes may overreport their exertion in an attempt to appear that they have already reached training load targets and to decrease the intensity of future training sessions. In summary, although sRPE is a valid method of measuring training load in hockey and can make individualized monitoring more accessible to hockey teams, there are several key limitations of sRPE, particularly when used without other monitoring methods. Coaches may overinterpret the results and athletes may inaccurately report scores, so, despite its validity, extreme care must be taken when using sRPE as a method of monitoring training load.

### 5.2.3 Correlations between Internal and External Training Load Measures

Although many published articles have reported both internal and external training load in hockey, this study is the first to examine the relationship between internal and external training load measures (Lythe, 2008; Boran, 2012; Abbott, 2016; Vescovi, 2016; McGuinness *et al.*, 2017). Previously, the correlation between TRIMP and total distance has been shown to be relatively strong in both men's professional football ( $r=0.78$ ) and international wheelchair rugby ( $r=0.84$ ) (Scott *et al.*, 2013a; William *et al.*, 2015). However, an even stronger relationship was found in this study, with fTRIMP scores being very strongly correlated with total distance ( $r=0.949$ ). Internal and external training load are distinct constructs, with no linear dose-response relationship expected between the two, as

one reports physiological load and the other physical output (Scanlan *et al.*, 2014). However, in this study, internal and external training load were very strongly correlated, indicating that 90% of the variation in total distance was explained by variation in fTRIMP scores.

Therefore, although internal and external training load are separate measures, the extremely strong correlation ( $r=0.949$ ) demonstrates that, in female hockey, internal training load, measured by fTRIMP, is a very good indicator of external training load, measured by total distance.

Although not as strong as the relationship between fTRIMP and total distance, there were also strong correlations between other measures of internal and external training load. Beginning with distances in speed zones, fTRIMP was most strongly correlated with distance covered in zone 3 ( $6.1-11.0 \text{ km}\cdot\text{hr}^{-1}$ ,  $r=0.910$ ) and zone 4 ( $11.1-15.0 \text{ km}\cdot\text{hr}^{-1}$ ,  $r=0.898$ ). Female TRIMP was not as strongly correlated with zone 5 ( $15.1-19.0 \text{ km}\cdot\text{hr}^{-1}$ ,  $r=0.821$ ), and much less so with zone 6 ( $>19.0 \text{ km}\cdot\text{hr}^{-1}$ ,  $r=0.542$ ). From one perspective, the fact that fTRIMP was best correlated with zones 3 and 4, rather than zones 5 and 6 may seem to indicate that distance covered at moderate speeds has the greatest impact on internal training load, rather than distance covered at high speeds. However, this result is confounded by the fact that the majority of total distance was covered in zones 3 and 4, and, as a result, these two zones were most closely related to total distance. Therefore, the increased correlations between fTRIMP and zones 3 and 4 were likely due to correlations between zones 3 and 4 and total distance, so it is important not to overinterpret this result. In addition to measures of distance, the relationship between internal training load and workrate was also considered. As workrate is a time-dependent measure and fTRIMP is a cumulative, non-time-dependent measure, it follows that the correlation between workrate and fTRIMP was low ( $r=0.300$ ). Similarly, one would expect to find that %MaxHR, another time-dependent measure, was more strongly correlated than fTRIMP with workrate ( $r=0.689$ ), and less strongly correlated than fTRIMP with total distance ( $r=0.430$ ). Therefore, when considering the relationship between internal and external training load measures, these results demonstrate the importance of comparing like-measurements, either both time-dependent or cumulative. Finally, in this study, team TRIMP was slightly more strongly correlated with all measures of external training load than iTRIMP. At first, this result may be counterintuitive since iTRIMP is fully individualized, and, as such, is often considered to be a more accurate measure of internal training load (Manzi *et al.*, 2009; Malone and Collins, 2016). However, since the external training load measures used were not individualized (speed zones were the same for all individuals), it follows that a non-individualized method of measuring internal

training load was more strongly correlated with external training load. Therefore, even though iTRIMP may be a more accurate measure of an individual's physiological response to exercise, team TRIMP is a better predictor of external training load.

From a practical perspective, the strong correlation between internal and external training load measures suggests that little information is lost when using only one form of athlete monitoring. Although heart rate and GPS monitors are becoming more integrated as the technology improves, in many cases, monitoring internal and external training load requires two distinct devices and software setups. For example, the Catapult 10 Hz GPS units and the Polar Team<sup>2</sup> heart rate monitors used in this study operated in isolation, requiring completely different equipment to be worn and software to be used. In fact, the internal and external training load data could only be analyzed simultaneously after they were separately downloaded into excel files and a Python 3.6 program, written by the researcher, was run on those files (Appendices E and F). Although just an anecdotal example, this demonstrates the difficulty of monitoring both internal and external training load. The extremely strong correlation between fTRIMP and total distance ( $r=0.949$ ) in this study suggests that little information will be lost by only using GPS monitoring. Specifically, for teams without the resources or patience to collect both internal and external training load, if external training load is collected using GPS, total distance can be used as an accurate predictor of internal training load. Therefore, coaches and analysts could forgo measuring internal training load and instead use the linearity of the relationship between total distance and fTRIMP to predict internal training load scores. However, as the somewhat weaker correlation between total distance and iTRIMP ( $r=0.882$ ) demonstrates, total distance is not a perfect predictor of internal training load, particularly when considering individual differences in the physiological response to exercise. Therefore, although the very strong correlation suggests that total distance is a good predictor of fTRIMP scores, it is important to remember that physical output and physiological load are distinct and no method of measuring external training load will perfectly substitute for measuring internal training load.

Overall, the interconnectedness of the various training load measures indicates that there are many valid methods of measuring internal and external training load in hockey, depending on the resources available and level of accuracy required. Firstly, the correlations between heart-rate based measures indicate that fTRIMP is an accurate predictor of iTRIMP and %MaxHR is closely related to fTRIMP. Therefore, although iTRIMP is the most individualized method of measuring internal training load, little information is lost by using the fTRIMP algorithm when lab-based fitness testing is not possible. Additionally, %MaxHR



measured over entire sessions is also highly correlated with team TRIMP and can be used as an accurate measure of internal training load, particularly if phasing and calculating TRIMP scores is not feasible. Furthermore, if measuring both internal and external training load is beyond the capabilities of a team, the strong linear correlation between total distance and fTRIMP suggests that total distance is an accurate predictor of internal training load. Finally, if no tracking equipment is available, the results of this study suggest that overall sRPE is a valid method of measuring training load, as it is very strongly correlated with both internal and external training load. Therefore, the correlations of the various training load measures indicate that regardless of the resources of a team, there are valid methods of individual athlete monitoring.

### 5.3 Training Load Measures and Fitness Outcomes

#### 5.3.1 Overall Fitness

Although there are many valid methods of measuring training load in hockey, not all methods are equal when it comes to predicting fitness. Specifically, unlike other measures of training load, team TRIMP, iTRIMP, %MaxHR, distance in zone 5 (15.1-19.0 km·hr<sup>-1</sup>), distance in zone 6 (15.1-19.0 km·hr<sup>-1</sup>), and effindex<sup>1</sup> (total distance: iTRIMP) were all relatively strongly correlated with fitness, as measured by individual average scores during lab-based fitness tests. It has been suggested that only measures that have an association with fitness or performance variables should be used as training load variables (Manzi *et al.*, 2009; Thomas, 2011). Therefore, the results of this study would suggest that of all the variables considered, team TRIMP, iTRIMP, %MaxHR, distances in zones 5 and 6, and effindex<sup>1</sup> are the only ones that should be used to monitor training load. Beginning with external training load, the moderate and strong positive correlations between fitness and distance covered in zones 5 ( $r=0.639$ ) and 6 ( $r=0.842$ ) indicate that the fittest athletes covered the greatest distances at high speeds. Notably, the correlation between fitness and total distance is not nearly as strong ( $r=0.358$ ), suggesting that the amount of high-speed running, particularly sprinting ( $>19$  km·hr<sup>-1</sup>), matters more than the total distance covered. Similarly, when considering individual average 30:15 scores as a measure of fitness, the results were similar, with even stronger correlations between fitness and distances covered in zones 5 ( $r=0.802$ ) and 6 ( $r=0.881$ ), yet still a much smaller correlation with total distance ( $r=0.431$ ). Therefore, although total distance may be a convenient measure of external training load, these correlations suggest that high speed running and sprinting distance are far better methods of

measuring external load. This result is likely due to the fact that, within reason, regardless of the distance covered, walking and slow running are not demanding enough to substantially affect fitness in elite athletes. As this study was observational, rather than experimental, it is impossible to determine if increased fitness led to more high speed running or if increased high speed running caused improved fitness. However, regardless of the mechanism, the very strong correlation, particularly between zone 6 and 30:15 fitness test scores ( $r=0.881$ ), demonstrates the strong relationship between sprinting and fitness and the importance of using this metric, rather than total distance, as a measure of external training load.

Moving on to internal training load, fTRIMP, iTRIMP, and %MaxHR were moderately to strongly correlated with lab-based fitness test scores. Specifically, the correlation of fitness to iTRIMP was the least strong ( $r=-0.662$ ), followed by fTRIMP ( $r=-0.740$ ), and %MaxHR ( $r=-0.832$ ). One may expect iTRIMP to have been more strongly correlated with fitness than team TRIMP or %MaxHR, as iTRIMP is more individualized; however, the results showed that just the opposite was the case. In fact, the least specific and sophisticated measure, %MaxHR, was the most strongly correlated with fitness scores, providing further evidence in support of %MaxHR as a valid measure of internal training load in hockey. Interestingly, when considering the results from the 30:15 fitness tests, the correlations between internal training load and fitness were extremely small (iTRIMP:  $r=-0.190$ ; fTRIMP:  $r=-0.162$ ; %Max HR:  $r=-0.310$ ). However, this may have been due to the fact that the 30:15 test is not as sensitive to small differences in fitness, with no credit being given for completing part of a level; therefore, less differentiation among athletes' fitness test scores may have led to lower correlations. Future research on the relationship between heart-rate based training load measures and fitness will be needed to verify these conclusions.

In addition to the strength of the correlations, it is important to note that the correlations between internal training load and fitness were negative. Therefore, these results, somewhat counterintuitively, indicate that the fittest athletes had the lowest internal training loads. One might expect the fittest athletes to have the highest physiological loads, as having increased physiological loads and exercising in higher heart rate zones generally increases fitness. However, the relatively strong negative correlations between internal training load and fitness shows that the fitter athletes had the lowest physiological loads. It is clear from the correlations between fitness and high speed running that even though the fittest athletes had lower internal training loads, they were still experiencing the highest physical loads. Therefore, the fitter athletes in this study had lower physiological loads not because of a decreased physical output but instead because their fitness level allowed them to sustain

higher physical loads than other athletes with lower physiological demands. In fact, the strong positive correlation of effindex<sup>1</sup> and fitness ( $r=0.785$ ) provides clear evidence for this conclusion, demonstrating that the fitter athletes were able to work more efficiently, performing a greater physical output with lower physiological demands than less fit athletes. Overall, fitness test scores were positively correlated with high speed running and sprinting distances, as fitter athletes performed a larger high-speed physical output than less fit athletes, while negatively correlated with measures of internal training load, as the increased efficiency of the fitter athletes meant that they were able to perform their elevated physical output with a lower physiological response.

### 5.3.1 Fitness Changes

When percent change in fitness is considered instead of absolute fitness test scores, there were only moderate correlations with three measures of training load, iTRIMP and distances covered in zones 5 and 6. Lab-based fitness test scores, rather than 30:15 scores, were used to determine percent fitness change, as the lack of sensitivity in 30:15 scores meant that many athletes demonstrated no change in 30:15 scores, despite there being notable differences in lab-based scores. Specifically, submaximal parameters, as measured during the lab test, have been shown to be more sensitive to training-induced changes than maximal measures (Impellizzeri, Rampinini and Marcora, 2005). Although not as strong as the correlations with absolute fitness test scores, iTRIMP ( $r=0.597$ ) and distance covered in zones 5 ( $r=-0.622$ ) and 6 ( $r=-0.663$ ) were moderately correlated with percent change in fitness. Examining just the strength of these correlations would suggest that these three measures of training load are the best for predicting fitness change. However, the correlations between fitness changes and distances covered in zones 5 and 6 were negative. This negative correlation is somewhat counterintuitive, as it suggests that athletes who do more high speed running and sprinting will have smaller fitness improvements over the course of the season than athletes who do less high speed running and sprinting. However, this result is confounded by the aforementioned correlations indicating that the fittest athletes performed the most high-speed running and sprinting (zone 5:  $r=0.639$ ; zone 6:  $r=0.842$ ). In fact, the fittest athletes had the smallest improvements in fitness over the course of the study, and there was a moderately strong negative correlation between lab-based fitness test scores at the start of the study and percent fitness change ( $r=-0.655$ ). Thus, athletes' fitness improvements were related to their fitness level at the start of the study, with fitter athletes

having smaller fitness improvements than less fit athletes, and this contributed to the negative correlations between fitness change and distances covered in zones 5 and 6.

Examining all the correlations together, it becomes apparent that the hockey season was not physiologically demanding enough for the fitter athletes to allow them to improve their fitness at the same rate as the less fit athletes. Although performing a larger physical output in terms of high speed running and sprinting than less fit athletes, fitter athletes also had lower physiological loads, demonstrated by the strong negative correlation between internal training load and fitness (iTRIMP:  $r=-0.662$ ; fTRIMP:  $r=-0.740$  %Max HR:  $r=-0.832$ ). As iTRIMP was moderately strongly correlated with fitness improvements ( $r=0.597$ ), the results of this study suggest that the lower internal training load in fitter athletes was associated with their smaller fitness changes over the courses of the study. Therefore, through the exact same matches and training which elicited large physiological loads and fitness improvements in the less fit athletes, the fitter athletes were not receiving high enough physiological loads to result in fitness improvements, despite their large physical outputs. Overall, this meant that fitness levels became more similar among the team as the season progressed, with a 16.5% decrease in the standard deviation of lab-based fitness test scores from pre-testing to post-testing. From a practical perspective, this result can be viewed as a success, as the goal of most coaches is to improve the fitness of their least-fit players to ensure that all athletes are adequately prepared for competition. However, on the other hand, these results also suggest that the physiological demands of training and competition were not high enough for the fittest athletes, and additional training would be required to ensure that these athletes were able to continue to improve their fitness rather than maintaining or dropping in fitness as the season progresses. This result provides further evidence in support of individualized athlete monitoring, since, despite completing an identical training and match protocol, athletes responded very differently from a fitness perspective.

In terms of individualized monitoring, the results of this study suggest that iTRIMP is the most effective method of monitoring training load to predict fitness change. Beginning with differential sRPE, there was almost no correlation between any of the sRPE scores and percent fitness changes (respiratory sRPE:  $r=0.103$ ; upper body sRPE:  $r=0.030$ ; lower body sRPE:  $r=0.017$ ; overall sRPE:  $r=0.160$ ). Although overall sRPE was relatively strongly correlated with measures of internal (fTRIMP:  $r=0.927$ ) and external training load (total distance:  $r=0.926$ ), when considered on its own, it provides little to no information on fitness change. Therefore, care should be taken when using sRPE, and results should be interpreted solely from a training load perspective, not as a predictor of fitness change. Moving on to

external training load, although there were relatively strong correlations between percent fitness change and distance covered in zones 5 ( $r=-0.622$ ) and 6 ( $r=-0.663$ ), these correlations were negative and confounded by the strong correlation between athlete fitness and distance covered in zones 5 ( $r=0.639$ ) and 6 ( $r=0.842$ ). Thus, future research will be needed on the relationship between high speed running and fitness changes. Finally, as the only training load measure that was moderately positively correlated with percent change in fitness ( $r=0.597$ ), iTRIMP was the best training load measure for predicting fitness change. In terms of fitness change, it is physiological load, not physical output that matters. For example, despite the physical output being the same, jogging one kilometer per day will have very different impacts on the fitness of a previously inactive individual compared to an elite athlete. Therefore, it follows that an internal training load measure will be the best predictor of fitness change. Additionally, as iTRIMP is the most individualized, it is the best suited internal training load measure to predict fitness change. The correlation between iTRIMP and fitness change is only moderate ( $r=0.597$ ); however, a strong correlation cannot be expected as many outside factors, such as nutrition, lifestyle, and sleep, will also impact fitness changes. Athletes are only monitored for a few hours each week, and actions taken outside of this time can have a large impact on percent fitness change. Thus, given the potential impact of outside factors, the moderate correlation ( $r=0.597$ ) indicates that iTRIMP is a very good training load measure for predicting fitness change.

Overall, the results of this study demonstrate the interconnectedness of the various training load measures, but also the distinct differences in the measures when it comes to predicting fitness and fitness change. Therefore, although there are multiple valid methods of measuring training load, it is important to select an appropriate measure, particularly if the aim is to predict fitness or fitness changes. Specifically, if one is interested in the relationship with overall fitness, all measures of internal training load as well as distances covered in zones 5 and 6 are good training load measures. However, if the aim is specifically to predict fitness changes, the results of this study suggest that iTRIMP should be used to measure internal training load. Although still valid methods of measuring load, other measures such as differential sRPE, total distance, workrate, and distance covered in lower speed zones were very weakly correlated with fitness outcomes, so care should be taken not to overinterpret these results as predictors of fitness or fitness change. Therefore, even though there were strong correlations between the various methods of measuring training load, there were notable differences in the relationships between training load measures and fitness.

## **Chapter 6: Discussion – Physical and Physiological Demands of Female British University Hockey**

### 6.1 Demands of Female British University Hockey Competition

This study was the first to summarize the demands of female British university hockey competition. The results, detailed in Table 4.7, demonstrate that although there are some similarities with other women's hockey populations previously studied, the demands of female British university hockey are unique.

#### 6.1.1 Playing Minutes

The average number of minutes played by participants in this study closely mirrors the minutes reported in other hockey populations. This is largely due to the fact that the game length and roster size in hockey is predetermined by the rules of hockey, as well as the regulations of the league or competition. For example, in the two leagues in which the participants of this study compete, England Hockey's National League North and British Universities & Colleges Sport's North A, competition consists of two 35-minute halves with roster limits of 16 athletes per match. Therefore, excluding the goalkeeper, there are 700 minutes of outfield play (10 athletes on the pitch at a time for 70 minutes) split among 15 athletes, resulting in a predicted average of 46.67 minutes. This predicted average is very close to the actual average of 46.95 minutes, with the slight difference likely due to the fact that not all fifteen outfield athletes were monitored during each game.

Four other studies have reported average minutes played during competition, with the results of this study falling in the middle of those previously published. The 47-minute average playing time in this study was notably higher than the 40.3 minutes previously published by Vescovi and  $44 \pm 7$  minutes reported by McGuinness et al. (Vescovi, 2016; McGuinness *et al.*, 2017). However, the Vescovi study considered U21 athletes, and most young adult tournaments permit squads of at least 18 rather than 16 (Vescovi, 2016). Similarly, the McGuinness et al. study included data from international test series, which usually have roster sizes of 18, so the larger roster size likely resulted in decreased minutes (McGuinness *et al.*, 2017). On the other hand, the results of this study are comparable to the previously published results of 46.7 minutes (Abbott, 2016) and  $48 \pm 4$  minutes (Macutkiewicz and Sunderland, 2011). These studies were both performed during international competition and included matches just before and during the 2014 World Cup and matches in the buildup

to the 2008 Olympics (Macutkiewicz and Sunderland, 2011; Abbott, 2016). As the roster limits for both the World Cup and the Olympics are 16 athletes, the squad size used during these matches was most likely 16 (Abbott, 2016). Therefore, in terms of average playing minutes, the results of this study are comparable to other hockey populations with roster sizes of 16 but not those with rosters of 18 athletes.

As average minutes is largely determined by game length and roster size, the standard deviation of playing minutes provides more information on the distribution of minutes across athletes. Specifically, the standard deviation of 10.2 minutes in this study was notably higher than the standard deviations of 4 minutes (Macutkiewicz and Sunderland, 2011) and 7 minutes (McGuinness *et al.*, 2017) previously reported in international hockey. This indicates that although the average number of minutes played was comparable to other female hockey populations with roster sizes of 16, those minutes were more unequally distributed across the athletes. In other words, rather than all athletes playing for a similar number of minutes, there was a greater disparity in the number of minutes played. Specifically, the minimum number of minutes played by an athlete in this study was 25.6 minutes and the maximum playing time was the entire match, a range of 36.6%-100% of total minutes. This large spread of playing minutes is likely due to the nature of university hockey, which involves a high rate of athlete turnover from season to season as athletes join or graduate from the university. One would expect a larger range of skill and fitness levels in a university side than an international team, where athletes are carefully selected and are often on the team for far longer than the 3 years that students usually play for their university. Therefore, the larger standard deviation of playing minutes may be caused by the fact that there is a larger disparity in skill and fitness levels among athletes, leading coaches to give more minutes to the strongest players and fewer to those not as far along in their development. Regardless of the cause, in terms of average minutes played, female British university hockey is similar to other hockey populations involving 16 athlete rosters; however, there is a larger standard deviation in minutes played, perhaps due to a greater disparity in skill level compared to international teams.

#### 6.1.2 Rating of Perceived Exertion (RPE)

The results of this study provide novel insight on RPE scores in hockey, as this study is the first to report RPE scores, more specifically differential sRPE, for hockey competition. To date, the only study that has considered sRPE in hockey investigated the correlation between heart rate and sRPE in youth hockey, with all measurements taking place during

training, not competition, and only correlations, not absolute results, being reported (Scantlebury *et al.*, 2017a). Therefore, there are no other hockey populations with which to compare the sRPE results of this study. However, considering just this study, it is clear that mean respiratory and overall sRPE scores are almost identical,  $301 \pm 93$  and  $300 \pm 87$ , with the mean lower body sRPE score being just slightly lower at  $293 \pm 92$ . This result indicates that athletes perceive overall exertion during competition to be very similar to respiratory and lower body exertion, suggesting that these mechanisms most contribute to fatigue. Similarly, the much lower score for upper body exertion,  $140 \pm 73$ , indicates that hockey competition is less than half as exerting on the upper body than on the lower body or respiratory systems. Although hockey athletes do use their upper body to control the movement of their stick, smaller upper body sRPE scores are to be expected as hockey primarily consists of running, with individual athletes spending little time with the ball in their possession.

In addition to considering the average values for sRPE, noting the very large standard deviations indicates that there was a large spread and little consensus on sRPE values in competition. There are several possible explanations for this occurrence. Firstly, since sRPE is calculated by multiplying the reported RPE score by time, and since, as discussed in the previous section, there was a large range of minutes played during matches, the variance in sRPE scores may have been due to variance in playing time. Additionally, RPE scores were collected from 10 participants, and, although all athletes were provided with the same rating scale, “hard” or “very hard” may have had a different meaning to each athlete. Therefore, some of the variation may have been caused by individual differences in the interpretation of the rating scale. Overall, the results of this study suggest that lower body and respiratory exertion levels are similar and comparable to the level of overall exertion experienced during hockey competition, but perceived exertion levels vary greatly.

### 6.1.3 Heart Rate

Average percentage of maximum heart rate (%MaxHR) values for female British university athletes were comparable to those of other athletes similar in age to the participants in this study, but higher than those in slightly older, adult hockey populations. Specifically, the average on-field %MaxHR of  $88.3\% \pm 3.1\%$  was only slightly higher than the published values of  $87.4\% \pm 3.5\%$  and  $87\% \pm 4\%$ , measured in US university hockey athletes and Canadian U21 athletes, respectively (Sell and Ledesma, 2016; Vescovi, 2016). Thus, the average %MaxHR of athletes during female British university hockey competition appears to be comparable in both magnitude and spread (given the similar standard deviations) to other



populations of university-aged athletes (18-22). On the other hand, athletes in international hockey competition, where average age was  $24 \pm 5$  years, have been reported to have lower average heart rates of  $85\% \pm 5\%$  and  $85.5\% \pm 2.9\%$  in female and male populations, respectively (Lythe, 2008; McGuinness *et al.*, 2017). These results are somewhat counterintuitive as one might expect the intensity, and subsequently the average heart rates, to be higher in international hockey than in younger hockey populations. However, the increased heart rates could be caused by lower levels of physical fitness and decreased tactical expertise in younger athletes. Regardless of the reason, the results of this study provide further evidence in support of slightly higher mean %MaxHR in university-aged hockey competition compared to adult international hockey.

In terms of TRIMP, no other study has reported Stagno's team TRIMP in a female hockey population, nor iTRIMP in any hockey population. As the units of TRIMP are arbitrary, the TRIMP scores themselves have little meaning unless there are benchmarks for comparison. Therefore, although the results of this study indicate an average iTRIMP score of  $199 \pm 63$  and an average fTRIMP score of  $223 \pm 28$ , more studies will be needed to provide context to these findings. To date, the only study considering TRIMP in a female hockey competition was the Vescovi study on Canadian junior international athletes (Vescovi, 2016). However, in this study, the weights from the Stagno study were utilized, but the zones cutoffs were modified, making an accurate comparison impossible (Vescovi, 2016). Considering men's hockey, as part of the study outlining the Stagno TRIMP algorithm, Stagno et al. reported an average TRIMP score of  $355 \pm 60$  during competition (Stagno, Thatcher and Van Someren, 2007). Clearly this value is much higher than any of the TRIMP scores reported in this study. However, it is important to consider that the  $355 \pm 60$  was calculated from an entire match, whereas the data presented in Table 4.7 represent only the time that athletes were on the pitch (Stagno, Thatcher and Van Someren, 2007). Removing the phasing from the data in this study and instead considering competition sessions as a whole, including warm-ups and time on the bench, gives much higher TRIMP scores, as presented in Table 4.12. However, even using the fTRIMP algorithm to adjust for the different physiological response in female athletes and measuring over entire competition sessions, the male athletes in Stagno et al.'s study still had a notably higher ( $355 \pm 60$ ) TRIMP score than the female athletes in this study ( $309 \pm 63$ ) (Stagno, Thatcher and Van Someren, 2007). These results indicate that the physiological demands of men's hockey may be greater than those of female hockey; although, more research measuring TRIMP in both male and female hockey populations will be needed to verify this conclusion.

In addition to comparing the TRIMP results of this study with other hockey populations, it is important to consider comparisons of the TRIMP scores recorded within this study. Firstly, in alignment with the results discussed in the previous chapter on the relationship between the fTRIMP algorithm and Stagno's algorithm, the ratio between the fTRIMP and Stagno's TRIMP scores is approximately 1.3, regardless of what segment of the game is considered. Furthermore, comparing the TRIMP scores for time-on-pitch only versus the entire game, including bench time, indicates that there is a significant load accumulated while athletes are on the bench. This result is in contrast with findings for non-time-dependent measures of external training load, such as total distance, which have been shown to not be significantly different (less than 5 m) when a full game versus a time-on-pitch analysis is utilized (White and MacFarlane, 2013). However, given that the body's physiological response to exercise does not cease as soon as the physical demand is over, it would follow that including time on the bench would lead to higher scores for cumulative internal training load variables. In other words, since an athlete's heart rates will still be elevated when the athlete comes off the pitch, it follows that including the entire match rather than just time-on-pitch will lead to higher TRIMP scores. Thus, although looking at only time-on-pitch is important for time-dependent measures such as average heart rate which could be skewed by resting time on the bench, in order to obtain a representative TRIMP score for the entire cumulative load of a game, it is important to include time on the bench in the analysis.

#### 6.1.4 Global Positioning System Parameters

Moving on to external training load, the demands of female British university hockey were similar to the demands of other female international hockey populations in terms of volume, but not workrate. Considering total distance covered, the average distance of  $5418 \pm 888\text{m}$  recorded in this study was comparable to the  $5540 \pm 521\text{m}$  and  $5541 \pm 1144\text{m}$  reported in previous studies measured across 39 and 13 international matches, respectively (Macutkiewicz and Sunderland, 2011; McGuinness *et al.*, 2017). Thus, these results suggest that the total distance covered in female British university hockey is similar to the distance covered in female international competition. Interestingly, although comparable to international competition, the average distance recorded in this study was notably lower than distances in other national level female competitions. Specifically, mean distances of  $6188 \pm 781\text{m}$ ,  $6600\text{m}$ , and  $6493\text{m}$  were measured in national level hockey in Ireland, Australia, and the US, respectively (Gabbett, 2010; Boran, 2012; Vescovi and Frayne, 2015). From one

perspective, this result is counterintuitive, as one might expect intensity and total distance to be greatest in international hockey competition. However, international hockey is more tactically advanced, so international teams' ability to maintain possession for longer periods may result in shorter total running distances, with the running that is occurring taking place at higher intensities. However, without considering the distances covered in various speed zones, it is not possible to know the paces at which distance is covered.

Breaking down total distance into distance covered in speed zones further suggests that the external demands of female British university hockey mirror those of female international competition. Specifically, as demonstrated in Table 6.1 below, the distance covered by participants in this study very closely mirrors the distances measured during a 2010 study of 25 female hockey athletes over the course of 13 international matches (Macutkiewicz and Sunderland, 2011). Specifically, the similarity of distances across all speed zones (apart from zone 1 which was not reported) demonstrates that not only were the athletes in this study covering a similar total distance to international athletes, but also that athletes were covering that distance at similar paces to those measured during international play (Macutkiewicz and Sunderland, 2011). Unfortunately, further comparison with other hockey populations is stymied by the lack of consistency in the speed zones used, demonstrating the need for a consensus on speed zone definitions in future research.

*Table 6.1: Distances in Speed Zones in British University and International Female Hockey (m)*

	<b>0-0.6</b>	<b>.7-6.0</b>	<b>6.1-11.0</b>	<b>11.1-15.0</b>	<b>15.1-19.0</b>	<b>&gt;19.0</b>
British University	54 ± 44	1415 ± 416	1772 ± 403	1306 ± 218	642 ± 154	229 ± 134
International	--	1653 ± 547	1780 ± 420	1226 ± 249	620 ± 172	232 ± 96

In addition to considering the similarities with other hockey populations, it is also important to examine the relationships between the individual speed zones within this study. Although, like most field-based team sports, the demands of hockey are intermittent, hockey is considered to be a high intensity game (Gabbett, 2010; Polley *et al.*, 2015; McGuinness *et al.*, 2017). With participants in this study averaging 88% of their maximum heart rate during competition, one might expect athletes to cover the majority of their total distance at relatively high speeds. However, athletes, on average, covered 59.8% of their total distance at speeds less than 11 km·hr<sup>-1</sup>, which is essentially walking or jogging. In fact, only 4.2% of total distance was covered at speeds greater than 19 km·hr<sup>-1</sup> (sprinting) and only 11.8% at 15-

19 km·hr<sup>-1</sup> (fast running). Thus, for a physiologically demanding game, the physical output of players, strictly in terms of speed, is relatively low. However, the semi-crouched position required for most hockey skills has been shown to increase heart rate and energy expenditure (Reilly and Seaton, 1990). Additionally, the need for explosive dynamic movement and the quick changes of speed and direction required are more physiological taxing than measures of speed or distance may suggest.

Also notable when considering the distance covered in speed zones are the relatively large standard deviation values, particularly for distance covered at speeds above 19 km·hr<sup>-1</sup>. This indicates that the actual distance covered at top speeds varied greatly among athletes. Specifically, distance covered over 19 km·hr<sup>-1</sup> during competition ranged from 58-780m, showing that some athletes sprinted far more than others. This disparity in sprinting distance is likely due in part to the differing demands of the various playing positions, which has been shown to significantly affect high speed running distance in national and international hockey populations (Gabbett, 2010; McGuinness *et al.*, 2017). However, more research will be needed to assess the positional impact on running speeds in female British university hockey.

As the amount of time that a hockey athlete spends on the pitch during competition varies, it is important to consider a relative, time-dependent measure of external training load in addition to the absolute measures. Considering workrate in meters per minute allows for comparisons across athletes who may have played for different minutes in a match. In terms of workrate, the results of this study suggest that the demands of female British university hockey are greater than those of similar-aged female hockey populations, but not as high as women's international competition. Specifically, studies on U21 Canadian and US university hockey athletes (age 18-22), reported workrates of  $112 \pm 6$  m·min<sup>-1</sup> and  $106$  m·min<sup>-1</sup>, notably lower than the  $117 \pm 10$  m·min<sup>-1</sup> measured in this study (Vescovi and Frayne, 2015; Vescovi, 2016). However, studies on female international hockey populations have reported average workrates of  $120 \pm 6$  m·min<sup>-1</sup> and  $125 \pm 23$  m·min<sup>-1</sup> (Abbott, 2016; McGuinness *et al.*, 2017). At first this lower workrate in British university hockey may seem contradictory to the aforementioned results on the similarity of total distance and distance in speed zones to international hockey. However, the variation in workrate is due to differences in average minutes played rather than differences in cumulative external training load (McGuinness *et al.*, 2017). For example, in the McGuinness *et al.* study, total distance covered over the entire match was only 122m higher than in this study, a difference of 2%; however, players in the McGuinness study averaged three minutes less playing time, resulting in their notably higher workrates (McGuinness *et al.*, 2017). As discussed in above, this difference in minutes

played was likely due to larger roster sizes. Overall, these results indicate that although the absolute external training load of female British university hockey mirrors that of female international hockey, both in terms of total distance and distance in speed zones, this work was performed over a longer average playing time, resulting in a lower average workrate.

#### 6.1.6 Efficiency Index (Effindex)

This study was the first to investigate efficiency index in hockey and to monitor changes in efficiency over the course of competition. The average value for effindex<sup>2</sup>, the ratio of workrate to %MaxHR, was 1.33. This value is consistent with findings in men's football, where two studies have reported effindex<sup>2</sup> to be 1.3 and 1.4 (Arrones *et al.*, 2014; Torreno *et al.*, 2016). Therefore, these results indicate that in competition, the efficiency of male football players is comparable to that of female hockey athletes; however more studies will be needed to confirm these findings. Values for effindex<sup>1</sup>, the ratio of total distance to iTRIMP, have never been measured and reported in a competition setting so, in the absence of other data, the mean value of 29.0 found in this study has little meaning.

While considering average effindex provides information on overall efficiency during competition, comparing effindex across halves provides more information on how efficiency changes throughout a match. Specifically, average effindex<sup>1</sup> decreased from 1.35 in the first half to 1.31 in the second half, a difference of about 3%, suggesting that athletes became less efficient over the course of competition. Although this is a relatively small difference, it does still suggest that athletes were not able to provide the same external output for a given physiological load as the game progressed. There are several possible causes for this decreased efficiency. The first and most obvious cause is that athletes became fatigued over the course of a match, and this increasing fatigue resulted in decreased efficiency. Increased fatigue may have been due to inappropriate substitution strategies that either had athletes on the pitch for too long during each individual stint, causing decreasing efficiency over the course of each stint, or provided athletes with inadequate recovery time between stints, causing efficiency to decrease from stint to stint. It is also possible that substitution strategies were not the problem and that the demands of hockey in this population are such that athletes will always become more fatigued and lose efficiency over the course of a match. In addition to fatigue, another possible cause of the decreased efficiency in the second half is that athletes were not adequately primed and physically prepared after halftime. In contrast to the first half, where athletes completed warm-up exercises up to about 2 minutes before the start of play, athletes were often stationary for most of the 7-10 minutes during halftime. As a result,

athletes began the second half after a period of inactivity and, therefore, may have been less efficient, particularly in the beginning of the second half when they were not appropriately warmed up and primed for competition. Re-warmup and activation techniques at the end of halftime may help to alleviate this issue. Finally, the decrease in efficiency in the second half of matches may be unrelated to fatigue or halftime activation and could instead be caused by increased psychological pressure and stress influencing physiology as the match progresses. Particularly in close games, as the game nears completion, there is increased pressure on athletes either to secure their lead or push ahead to win. This increased stress may cause athletes to have elevated heart rates, thus decreasing their efficiency. Overall, without more research, it is not possible to know the exact cause of the decreased efficiency in the second half; however, fatigue, inadequate halftime activation, and psychological stress may all be contributing factors.

In summary, the results of this study indicate that although there are some similarities with other hockey populations, the demands of female British university hockey competition are unique. Specifically, average %MaxHR was found to be comparable to that measured in other young adult hockey populations but higher than heart rates recorded in international hockey. In terms of external training load, total distance and distance in speed zones were very similar to distances measured in international hockey populations. However, athletes in this study played more minutes per match, resulting in lower workrates. In addition, differential sRPEs indicated that lower body exertion and respiratory exertion during match play were comparable and contributed most to overall exertion. Finally, effindex scores suggests that player efficiency in women's hockey is comparable to player efficiency in men's football, and efficiency decreases from the first half to the second half during competition.

## 6.2 Overall Season Demands

Considering training in addition to competition provides information on the overall physical and physiological demands of a hockey season. In the female British university population studied, each week consisted of two training sessions as well as two matches, and the season was made up of two halves, each eight weeks long. Athletes also participated in a six-week preseason prior to the first half of the season and a one-week preseason prior to the second half of the season; however, these pre-season periods were not fully monitored and were not included in this analysis. Although many studies have examined the demands of hockey competition, only one other study has considered the demands of a hockey season as

a whole (Stagno, Thatcher and Van Someren, 2007). In fact, almost all of the studies that have monitored both training and competition have been performed on international athletes, who have no regular in-season and out-of-season periods (Gabbett, 2010; Polglaze *et al.*, 2015; White and Macfarlane, 2015a; White and Macfarlane, 2015b). The one study that did consider season loads reported a mean weekly TRIMP score of  $826 \pm 123$  for male athletes competing in the English Premier League (Stagno, Thatcher and Van Someren, 2007). This result is slightly higher than the average weekly Stagno TRIMP score of  $695 \pm 86$  recorded for the athletes in this study. However, as discussed in the previous chapter, the Stagno TRIMP algorithm underestimates training load in female populations, so the fTRIMP score of  $902 \pm 110$  provides a more accurate value for comparison to Stagno TRIMP in male populations. Therefore, these results suggest that the average weekly physiological demands of female British university hockey are somewhat greater than those of the men's English premier league. Although one might expect the weekly training load associated with playing in the premier league to be greater than that of university athletes playing in the national league (one level below the premier league), university athletes play an additional match per week (Stagno, Thatcher and Van Someren, 2007). As Stagno et al. showed that TRIMP scores were significantly higher in competition than in training ( $p < 0.001$ ), it follows that by playing an additional match per week, university athletes will accumulate a higher weekly internal training load (Stagno, Thatcher and Van Someren, 2007). Unfortunately, season external training load was not considered during the Stagno et al. study, nor in any other study to date, so it is not possible to determine how the average weekly external training load measured in this study compares to loads in other hockey populations (Stagno, Thatcher and Van Someren, 2007).

### 6.2.1 Mean Weekly Training Load

Although comparison with other hockey populations is not possible, considering external training load measures in this study provides insights on the intensity and demands of the British university hockey season. Beginning with total distance, athletes covered, on average, 23.44 km per week which, over the 16-week season, is a total of 375 km. However, very little of this running was performed at top speeds, with only 0.71 km (3%) covered each week at speeds over  $19 \text{ km}\cdot\text{hr}^{-1}$  and 2.64 km (11%) at speeds greater than  $15 \text{ km}\cdot\text{hr}^{-1}$ . The majority of the total distance, 16.63 km (71%), was covered at speeds of  $11 \text{ km}\cdot\text{hr}^{-1}$  or less, with 9.72 km (41%) covered at speeds of  $6 \text{ km}\cdot\text{hr}^{-1}$  or less, which is essentially walking. Therefore, although hockey is considered to be a high intensity sport, much of the athletes'

overall season load was actually performed at relatively low speeds. However, given that the data here represent cumulative loads over the course of entire training sessions and matches, these values include walking and jogging performed while warming up, collecting balls, in-between drills, on the sideline of a match, or during half-time. When this in-between time is phased-out and only active time either on the pitch or in a training drill is considered, the average weekly distance covered at  $6 \text{ km}\cdot\text{hr}^{-1}$  or less drops from 9.72 km down to 4.28 km, while, as a comparison, total distance covered at speeds greater than  $19 \text{ km}\cdot\text{hr}^{-1}$  only drops 0.10 km. Therefore, although there is still a reasonably large distance covered at low speeds, when only active time is included, this distance is much lower than the unphased cumulative season loads would suggest.

In addition to external training load, considering minutes played and sRPE also provides information on the overall demands of a hockey season. In terms of timing, athletes spent  $396.6 \pm 15.8$  minutes, just over six and a half hours, in training and competition each week. However, of these  $396.6 \pm 15.8$  minutes only  $134.5 \pm 18.4$  minutes were spent either on the pitch during competition or in active, small-sided-game type drills in training. Therefore, although athletes spent over six and a half hours on the pitch each week, only one-third of this time was active. This result suggests that if athletes or coaches would like to save time and decrease the amount of time that athletes are on the pitch, it is possible to do so without decreasing active minutes. However, it is also important to note that although there is a lot of non-active time, this time includes warm-ups, halftime, tactical instruction between drills, and time spent in stationary drills, such as penalty corner practice. Finally, moving on to sRPE, the trend of sRPE scores for an average week mirrors that of sRPEs on match days. Specifically, lower body, respiratory, and overall sRPE scores are all very similar,  $796 \pm 149$ ,  $817 \pm 154$ , and  $813 \pm 143$ , respectively, indicating that the level of respiratory and lower body exertion over the course of a hockey season are comparable to overall levels of exertion. Furthermore, the mean upper body sRPE score,  $400 \pm 158$ , is about half that of lower body, respiratory, and overall scores, indicating that athletes find a hockey season to be about half as exerting on the upper body than on the lower body or respiratory system.

### 6.2.2 Variation in Individual Weekly Load

Up to this point, season load has only been discussed in terms of mean values across all athletes in the study; however, it is also important to consider the variation of average weekly load in individual participants. Specifically, the relatively large standard deviation values and ranges for many of the training load measures indicate that although all



participants in this study were members of the same team and were monitored during the same matches and training sessions, the actual load performed varied significantly between athletes. For example, average weekly fTRIMP score calculated using the new female algorithm ranged from 614-1057. Therefore, the participant with the highest fTRIMP value averaged a score 172% higher than the individual with the lowest fTRIMP score. Over the course of the 16-week season, this weekly variation in TRIMP results in a massive difference in the physiological load on athletes. As the heart rate versus blood lactate curve varies in individuals, this large range of TRIMP scores may appear to be due to individual variation in the physiological response to exercise. However, considering iTRIMP scores, which completely control for the individual differences in heart rate versus blood lactate curves, the range of scores is even larger, 448-1105. Additionally, average percent of maximum heart rate during time-on-pitch or time spent in active training drills varies from 81.5% to 90.5%, further suggesting that the actually physiological workload differs greatly in individual athletes. Finally, sRPE scores are also notably varied with average weekly lower body, upper body, and respiratory sRPE ranging from 561-1016, 130-702, and 573-1008, respectively. However, as individuals may have had different interpretations of the RPE scale that was provided, it is difficult to determine if this range is due to variation in actual physiological load or in individual interpretations of the exertion scale rankings.

In addition to the range in physiological load, there is also a large variation in the intensity of the physical output performed by athletes in this study. The average weekly total distance covered was relatively similar across all athletes with a range of only 21.61-24.98km. However, weekly average distance covered at speeds greater than  $19 \text{ km}\cdot\text{hr}^{-1}$ , essentially sprinting, varied from 456m to 1209m. Therefore, the athlete who sprinted the most sprinted over two and a half times as much as the athlete who sprinted the least. Over the course of the 16-week season this amounts to a difference of 12.0 km covered at speeds greater than  $19 \text{ km}\cdot\text{hr}^{-1}$ . In addition, average workrate while on the pitch in matches or in active drills ranges from  $96.2 \text{ m}\cdot\text{min}^{-1}$  to  $119.9 \text{ m}\cdot\text{min}^{-1}$ . Although some of this variation will be related to the number of minutes played, the average difference of 23.7m covered every minute further demonstrates the variation in the intensity of physical output among athletes. Finally, average effindex<sup>1</sup>, the ratio of total distance to iTRIMP, ranges from 20.6 to 44.8 for athletes in this study. This large range could be due to differences in the intensity of physical output, as previously discussed, with some athletes covering distances at much lower speeds so not eliciting the same physiological response as other athletes, or could be linked to differences in fitness, with fitter athletes able to perform the same external load while

eliciting a lower physiological response. Overall, these results demonstrate that athletes on the same team, participating in the same trainings and matches, do not necessarily receive a similar physical or physiological training load.

There are several factors that likely contributed to the variation in individual training load over the course of the season. Firstly, several studies have shown that playing position results in significant differences in internal and external training load during hockey competition (Gabbett, 2010; Jennings *et al.*, 2012a; Boyd, Ball and Aughey, 2013; Vescovi and Frayne, 2015; Abbott, 2016; McGuinness *et al.*, 2017). For example, workrate has been shown to be significantly higher in midfielders and forwards than in defenders ( $p<0.05$ ) (Boyd, Ball and Aughey, 2013; Abbott, 2016; McGuinness *et al.*, 2017), and time spent above 85% of maximum heart rate was found to be significantly higher in defenders than in midfielders or forwards ( $p<0.001$ ) (McGuinness *et al.*, 2017). Additionally, midfielders have been repeatedly shown to cover greater distances at high speeds than either defenders or forwards (Gabbett, 2010; Jennings *et al.*, 2012a; Vescovi and Frayne, 2015; McGuinness *et al.*, 2017). Therefore, the variable demands of playing positions likely contributed to the large range of average weekly loads. In addition to playing position, another possible explanation for the large range of training load values is a disparity in effort levels. As the large range of sRPE scores would suggest, some athletes may have exerted themselves more in training and matches, working harder to attack and defend on the field and, as such, covered greater distances at high intensities and had higher internal training load scores. Finally, the variance in athlete fitness levels likely contributed to the large range of training load scores. As discussed in the previous chapter, fitness scores were strongly correlated with distances covered in zones 5 ( $r=0.639$ ) and 6 ( $r=0.842$ ) and effindex<sup>1</sup> ( $r=0.769$ ) suggesting that the range of fitness levels contributed to the spread of training load scores.

Regardless of the cause, the large range of training load scores indicates that hockey athletes who participate in the same trainings and matches do not always receive comparable training loads. This result provides clear evidence in support of individualized monitoring to ensure proper training doses are met. Without individualized monitoring, it would be impossible to determine the quantity of work each athlete performed, causing some athletes to overtrain and others to undertrain, all while completing the exact same sessions. Individualized monitoring, whether of internal or external training load, allows coaches and sports scientists to develop individualized training protocols, providing rest to some athletes while prescribing extra sessions to others, and this has been shown to improve fitness, prevent injuries, and improve competition performance in team-sport athletes (Foster *et al.*,

2001; Liu *et al.*, 2013; Kevin and James, 2015; Mara *et al.*, 2015; Bourdon, 2017). As the sixteen-week hockey season that British university athletes complete is relatively long, even small variations in average weekly load results in sizable differences in overall load by the end of the season. As previously discussed, distances covered in zones 5 ( $r=0.639$ ) and 6 ( $r=0.842$ ) were correlated with fitness test scores, and iTRIMP was moderately correlated with percent fitness change ( $r=0.597$ ). Therefore, careful individualized monitoring over the course of the season is important to control for variation in training load as it occurs to help ensure that athletes reach target fitness levels.

### 6.3 Demands of Training vs. Competition

The results of this study indicate that the physical and physiological demands of training are not comparable to the demands of competition in female British university hockey. Specifically, all measures of training load were found to be significantly higher in competition than in training ( $p<0.01$ ) with a large effect size ( $d>0.8$ ), indicating that training is not as demanding as competition. These findings are in alignment with the results of previous studies on the differences between hockey training and competition, which have reported significantly lower workrates and less high speed and moderate speed running in training than in competition ( $p<0.05$ ) (Gabbett, 2010; Polglaze *et al.*, 2015). Therefore, the results of this study provide further evidence on the physical differences between training and competition and demonstrate that there is a corresponding physiological difference as well.

As training sessions often consist of many different elements, it is important to consider the makeup of the training sessions included in this analysis. Training sessions in this study generally consisted of three main elements: technical skill warmup, small-sided games, and penalty corner practice, most often performed in that order. After a physical warm-up, the athletes would perform a technical skill warmup which consisted of various passing patterns, ball-carrying skills, and, on some occasions, a shooting drill. Following this warm-up, athletes would perform one or more small-sided games that would last for most of the training session. Specifically, small-sided games are any type of training drill in which a reduced number of athletes play a game in a designated area with various rules and constraints (Polglaze *et al.*, 2015). Finally, training sessions would conclude with relatively stationary penalty corner practice. In this analysis, only small-sided games were included in order to control for and exclude the stationary aspects of training. As small-sided games are designed to mirror aspects of competition and are frequently used for conditioning, these types of drills are most appropriate for comparison to gameplay (Polglaze *et al.*, 2015).

Although removing the other aspects of training does remove a large portion of training data, the aim of technical drills and penalty corners is skill acquisition. As such, these drills are not intended to mirror the demands of match play, and a comparison would be inappropriate. Additionally, games data were edited to include only time-on-pitch, so a large portion of match data, such as warmup prior to the game, time on the bench, and halftime, was also excluded. Therefore, by phasing the data, extraneous information was removed so that only the elements of training and matches that were designed to be similar could be compared.

Despite the fact that only small-sided games were included in the analysis, the results of this study still showed that the demands of training were significantly different than the demands of competition. One of the most notable differences between training and competition is time, with athletes spending, on average, 47.0 minutes active in competition, while only 21.2 minutes active in training. This result suggests that although training sessions typically lasted between one and one and a half hours, only a small amount of this time was actually spent active in small-sided games, and, as such, the volume of training was less than that of match play. Since athletes spent more than twice as long active in competition than in training, it would follow that absolute, non-time-dependent measures, such as distance and TRIMP would be significantly lower in training, as the results indicate. The amount of time spent active in training was simply not long enough for athletes to achieve the load reached during matches. However, in some cases, the lower number of active minutes in training may have been intentional and appropriate. For example, the athletes in this study trained on Friday mornings prior to matches on Saturdays. In this instance, coaches did not intend for athletes to perform the same volume of work that they would on a matchday, but, for the small amount of time that they were active in drills, the aim was still to mirror the intensity of competition.

Comparing relative training load measures indicates that not only was the overall volume lower in training than in competition, but the intensity of the work performed was also lower. Considering time-dependent measures, such as %MaxHR and workrate controls for differences in time between training and competition and provides an indication as to the physical and physiological intensity of the work taking place. The p-values of less than 0.0001 and large Cohen's d values for these measures (.86 and 1.1) demonstrate that not only were athletes not working for as long during training, they were also not working as hard, physically or physiologically. Additionally, dividing other training load measures by time, so that they can be considered as relative measures, provides further evidence that the intensity of training does not match the intensity of competition. For example, dividing fTRIMP

scores by time yields values of  $4.75 \text{ AU}\cdot\text{min}^{-1}$  for competition and  $3.76 \text{ AU}\cdot\text{min}^{-1}$  for training, a difference of 26%. Furthermore, considering high speed running ( $>15 \text{ km}\cdot\text{hr}^{-1}$ ) per minute, athletes covered  $18.6 \text{ m}\cdot\text{min}^{-1}$  during competition and  $13.6 \text{ m}\cdot\text{min}^{-1}$  in training, a difference of 36.9%. Overall these results indicate that in terms of both total volume and intensity, the demands of hockey training are not comparable to the demands of hockey competition in this population.

As the most effective form of training in team sports has been shown to be that which best mirrors the movement patterns and intensity of competition, these results suggest that for the female British university hockey athletes in this study, training may not be adequately preparing them for competition (Liu *et al.*, 2013; Abbott, 2016). Since the intensity of training is significantly lower than that of competition, athletes will face greater physical and physiological demands during matches than in training. Athletes may struggle to play and make smart decisions under the level of strain and fatigue in competition, as it is not something that they regularly experience in a training environment. For the athletes participating in this study, the lack of intensity in training may not be a large issue, as athletes play two matches per week and, as a result, will have plenty of experience playing at high intensities during matches. However, as training was still used to practice various tactics, skills, and scenarios, the lack of intensity in this environment meant that training was less effective, and athletes were not fully prepared to execute what they had learned in training at the intensity required for competition. Thus, the results of this study suggest that coaches and athletes should increase the intensity of training sessions. There are countless ways to increase intensity, including everything from verbal encouragement or adding punishments for the losing team to modifying the rules of small-sided games. Making the playing area larger or reducing the number of players involved in a drill will likely increase intensity. Additionally, if training sessions are scheduled close to competition, using very short, high-intensity periods for small-sided games could control for overall volume while still ensuring athletes are adequately prepared for competition. Regardless of the method used to increase intensity, the results of this study show that unless intensity is increased in training, training will not be most effectively preparing the athletes in this study for the physiological and physical demands of competition.

## 6.4 Study Limitations

### 6.4.1 Sample Size

As is often the case in team sports research, a major limitation of this study was the small sample size. It has been suggested that the ratio of subjects to dependent variables should be, at minimum, no less than 3 to 1 (Vincent, 1999). With 18 dependent variables and only 10 subjects for most of the study, this ratio was clearly not upheld. Although, data for these individuals were collected across 24 sessions, resulting in 235 sessions monitored (5 sessions missing due to injury absence), the statistical power was still limited by the number of subjects. As a British university hockey team never consists of more than 15 outfield players, it would be impossible to obtain the recommended subject to dependent variable ratio within a single hockey team. Although a cross-sectional study of a league or region would provide a broader perspective and much greater statistical power, it was simply not feasible with the time and resources available to the researcher. Since all athletes were from one team, not a representative sample of all elite female British university hockey teams, these results cannot be fully generalized to all British university hockey populations.

The original intent of this study was to include as close to 15 outfield members of the Durham University Hockey Club's Women's First Team as possible. The study commenced with 17 participants with the goal of including all participants who would regularly train and play for the first team, as selections vary from week to week. However, due to a variety of uncontrollable factors, not enough data were able to be collected from all participants for them to be included in the final analysis. For example, several athletes had international playing commitments requiring them to miss large sections of the season. Furthermore, other players were alternately dropped to play in the second team, as experienced players returned from injury and outside commitments. These athletes with mostly incomplete data sets were excluded from the final analysis to prevent their data skewing the results, as it was impossible to accurately determine average loads given the extent of their absences. In the end, participants were included in the final analysis if they had over 80% complete data sets, including RPE, heart rate, and GPS data measured across all sessions.

### 6.4.2 Missing Data

As touched on in the previous section, missing data was another challenge faced during this study. Even among the participants who were included in the final analysis and

had over 80% complete data sets, there were still whole sessions or aspects of sessions, be that RPE, heart rate, or GPS, that were missing. A variety of reasons contributed to missing data. Device malfunction and operator error caused the greatest number of missing data sets. Although participants were provided with full instructions and demonstrations on how to turn on and wear their monitoring equipment, there were several cases where individuals forgot to turn on their GPS device or wore their heart rate monitor incorrectly. Prior to the study, all heart rate monitors and GPS units were fully tested to ensure their proper functioning; however, throughout the study, several of the heart rate monitors stopped holding a charge and downloading properly. These monitors were swapped out for new devices, but accurate data were unable to be retroactively obtained from the sessions during which the malfunctioning monitors were worn. Finally, other missing data resulted from players missing a training session due to injury, which occurred 4 times, or not reporting RPE, despite receiving two reminders from the researcher. To control for missing data, training loads were averaged across all sessions of similar type (for example Monday night training or Wednesday matches), and these averages were then summed or averaged, depending on the metric, to provide an average weekly load. Although it would have been preferable to have complete data sets for all individuals, this method of analysis minimized the effect of missing data, making this only a minor limitation.

In addition to missing data from training sessions or matches, the study was unable to completely control for training performed by athletes outside of scheduled team sessions. Ideally, all participants would have worn their heart rate and GPS monitors during any outside training performed. However, as devices had to be collected following each training session for charging, data download, and secure storage, participants were not able to keep their monitors and wear them during any extra sessions they may have chosen to perform. To alleviate this issue, all participants were asked to fill out a separate survey including a description, the length, and RPEs for any outside training sessions performed. Although participants were repeatedly reminded of this survey and the importance of recording outside sessions, there were only two sessions recorded in this manner by athletes included in the final analysis, and the researcher was later made aware that some outside training occurred but was not recorded. At that point it was too late for participants to go back and accurately recall RPEs and length of the sessions, so, unfortunately, these data were not able to be collected.

#### 6.4.3 Testing Errors

Although many efforts were taken to minimize testing errors, it was not possible to control for all confounding factors that may have influenced athletes' fitness test scores. Firstly, athletes were not monitored prior to the start of testing, so they were on their honor to complete the pre-testing protocols. Specifically, athletes were asked to abstain from alcohol and strenuous physical activity for 24 hours prior to fitness testing and were given reminders of this requirement in the days leading up to testing; however, without constant monitoring, it was not possible for the researcher to ensure that these requirements had been met. Additionally, some athletes mentioned to the researcher that they had been ill and were not feeling well during post-testing. Post-testing was pushed back several days for these individuals to allow for recovery; however, due to participants' scheduling constraints approaching the holidays, there were limited options for post-testing dates.

Another possible confounding factor during the 30:15 fitness test was athletes' motivation level. As athletes can drop out at any time, it is not possible for the researcher to ensure that athletes truly gave a maximal effort instead of dropping out early due to building fatigue and a lack of motivation. Additionally, as no partial scores are given and athletes must compete an entire level to receive credit for it, the test is not very sensitive to small changes in fitness. Knowing this, despite verbal encouragement, during the post-test some athletes did not even attempt to start the level higher than that which they completed in the pre-test, believing that they would not make it through the full 30 seconds. As a result, only 50% of the athletes in the study changed their 30:15 score from pre to post-testing. Of those athletes who did receive a different score, no one differed by more than one level, despite athletes' lab-based fitness test scores indicating larger fitness changes. Thus, these results suggest that motivation and athletes' self-belief may have influenced their 30:15 scores.

#### 6.4.4 Other Considerations

Another limitation of this study on female athletes was that the effect of participants' menstrual cycles was not considered. The exact effects of the menstrual cycle on exercise performance is unclear, with several reviews highlighting the mixed results of previous research studies (Jonge, 2003; Oosthuyse and Bosch, 2010; Tsampoukos *et al.*, 2010). The hormonal fluctuations over the course of the menstrual cycle have been shown to impact fat metabolism, carbohydrate utilization, and body temperature, all of which can impact athletic performance (Jonge, 2003; Oosthuyse and Bosch, 2010). Furthermore, more outright symptoms, such as cramping, headaches, bloating, or iron deficiency from heavy blood loss



also influence athletes (Bossi *et al.*, 2013). Lactate threshold, as was measured during lab-based fitness testing in this study, has been shown to not be significantly different during various stages of the menstrual cycle in university athletes ( $p>0.05$ ) (Bossi *et al.*, 2013; Ross *et al.*, 2017). However, a 2017 study on female university football found that performance during the Yo-Yo intermittent endurance test, a maximal on-field fitness test similar to the 30:15 fitness test, was considerably lower ( $p=0.07$ ) during the mid-luteal phase compared to the early follicular phase (Ross *et al.*, 2017). These results suggest that athletes' 30:15 scores may have been impacted by the phase of their menstrual cycle. Nevertheless, with 55% of British women ages 18-19 and 52% of British women ages 20-24 using oral contraceptives, it is likely that many of the study participants would have been taking oral contraceptives, which reduce hormonal variations over the course of the menstrual cycle (NHS Digital, 2017).

Weather and time of day are other factors that may have influenced athlete performance over the course of the study. Circadian rhythm has been shown to influence exercise performance, with daily fluctuations in body temperature and hormone levels affecting performance levels throughout the day (Weipeng, Michael and Michael, 2011). Training sessions and matches took place at approximately the same time each week, thus minimizing the effects of circadian rhythm on training load data collected during the sessions. However, despite efforts being taken to ensure that athletes' pre-study and post-study fitness testing took place at the same time, due to scheduling constraints, performing testing at precisely the same time was not always possible. Additionally, as hockey is an outdoor sport, and all activities, except for the lab-based fitness test, took place outside, weather may have impacted athlete performance and training load. For example, when performing hockey skills in high temperatures (30°C) heart rate has been shown to be significantly higher ( $p<0.05$ ) than when performing those same skills at moderate temperatures (19°C) (Sunderland and Nevill, 2005). As this study took place in Northern England, athletes did not experience high temperatures but rather low temperatures (about 3°C) and high winds during some training sessions. No study has considered the impact of cold temperatures on hockey performance; however, research in football suggested that cold temperatures ( $<5^{\circ}\text{C}$ ) did not impact match-action profiles (Carling, 2011). On the other hand, wind resistance has been shown to significantly impact sprinting performance ( $p<0.001$ ) (Moinat, Fabius and Emanuel, 2018). Therefore, weather conditions, particularly wind, may have been a confounding factor in this study. Overall, the limitations of this study provide areas for improvement in future studies on female hockey athletes.

## Chapter 7: Conclusion

The aims of this research study were (1) to investigate the various methods of measuring training load in female hockey athletes and (2) to quantify the demands of female British university hockey. With relevance to these aims, the conclusions to the four research questions are given below.

### *1) Are there associations between different methods of measuring of training load in female hockey athletes?*

Yes, there were strong linear relationships between many of the various methods of measuring training load in the female hockey athletes monitored in this study. Overall sRPE was very strongly positively correlated with other measures of internal and external training load, suggesting that overall sRPE is a valid perceptual measure for monitoring training load. Stagno TRIMP and fTRIMP scores were very closely related, summarized by a multiplicative factor of 1.3, demonstrating the importance of not applying male monitoring protocols to female athletes without adjusting for sex differences. In addition, total distance and fTRIMP were strongly correlated indicating that total distance could be used to predict internal training load if only external training load is measured. The interconnectedness of the various training load measures suggests that there are multiple valid methods of measuring training load in female hockey, including easily obtained measures such as sRPE and %MaxHR, as well as more complicated measures such as iTRIMP and GPS metrics. Overall, these results demonstrate that regardless of the resources of a team, there is a valid method of monitoring training load that can be used to individualize training protocols.

### *2) Which training load measure(s) best predicts fitness and fitness change?*

Distance covered in zones 5 and 6 and effindex<sup>1</sup> were the best predictors of athlete fitness and iTRIMP was the best predictor of fitness change. The fitter athletes in this study were able to complete training and matches with lower physiological loads, despite their increased high speed running and sprinting outputs and showed smaller increases in fitness. Thus, despite the elevated physical outputs of the fitter athletes, their increased efficiency meant that training and matches were not physiologically demanding enough for them to improve their fitness at the same rate as less fit athletes. These results reinforce the need for individualized athlete monitoring as all athletes were performing the exact same training sessions and matches, and, without individualized monitoring, it would have been impossible to determine the variations in load that impacted athlete fitness levels in this study.

Furthermore, the results of this study demonstrate that if the goal is to predict fitness change or overall fitness, iTRIMP, distances covered in zones 5 and 6, or effindex<sup>1</sup> should be used to measure training load, instead of other measures less associated with fitness outcomes.

*3) What are the physical and physiological demands of female British university hockey and how do these demands compare to other previously studied female hockey populations?*

Comparisons of competition demands with other previously studied female hockey populations demonstrate that despite some similarities, the demands of female British university hockey are unique. In terms of internal training load, %MaxHR measured in this study was comparable to that measured in other young adult hockey populations, but higher than values reported during international competition. Considering external training load, total distance and distance in speed zones were comparable to values previously reported in female international hockey, but athletes in this study averaged more playing minutes per match than international athletes, resulting in lower workrates. In addition to the average values, the results of this study showed that there were large variations in athlete loads both in competition and over the season as a whole. These results demonstrate that athletes who participate in the same training and matches will often receive noncomparable loads. Overall, the uniqueness of and variation in the demands of female British university hockey demonstrate the need for individualized athlete monitoring in this population.

*4) How do the demands of training compare to the demands of competition?*

The physical and physiological demands of training were significantly lower than the demands of competition for all training load measures. As the most effective form of training for team sports has been shown to be that which mirrors the intensity and demands of competition, these results suggest that the small-sided games used in training were not adequately preparing the athletes in this study for competition (Liu *et al.*, 2013; Abbott, 2016). Therefore, modifications to training need to be made and more individualized monitoring will be needed to ensure that future training exercises mirror the demands of competition in female hockey.

In conclusion, the results of this study demonstrate the need for individualized monitoring in hockey and provide detailed information on the various methods of measuring training load. The demands of training were shown to be significantly lower than the demands of competition, demonstrating the need for athlete monitoring during training to

ensure that athletes are working at adequately high intensities to prepare them for the demands of competition. Additionally, the very large ranges and standard deviations both in individual match load and average weekly load show that hockey athletes participating in the exact same training and competition sessions often have vastly different training loads. As high speed running and sprinting distances have been shown to be closely associated with athlete fitness, and iTRIMP scores to be a predictor of fitness change over the course of the season, the results suggest that the variation in athlete training load will be associated with changes in athlete fitness outcomes. Therefore, individualized monitoring is needed to ensure that all athletes are receiving appropriate training doses to achieve target fitness and performance outcomes. Fortunately, the results of this study have shown that there are many valid methods of measuring training load, depending on the resources of a team and the level of accuracy required. Additionally, a factor of 1.3 was established between male and female team TRIMP scores to allow for comparisons across sexes. Future experimental studies will be needed to determine training load thresholds for target fitness and performance levels; however, correlations with fitness outcomes in this study suggest that iTRIMP, effindex, and distance covered in zones 5 and 6 are the training load measures best suited for developing these thresholds. Overall, this study provides clear evidence in support of individualized athlete monitoring in female hockey to ensure that athletes achieve appropriate training doses and suggests the training load measures most appropriate for this monitoring. As individualized monitoring can improve fitness as well as increase performance and reduce overuse and fatigue-based injuries, the results of this study can be used to improve female hockey overall, reducing the risk of athlete injury while simultaneously increasing the level of athlete performance.

### *Future Directions*

The four research questions addressed in this study bring to light several areas for future research in this field. Firstly, since this study was the first to measure differential sRPE, fTRIMP, iTRIMP and effindex in hockey, more studies will be needed to further validate these methods of monitoring training load in various hockey populations. Additionally, as there was a clear multiplicative relationship measured between the male-based Stagno and female-based fTRIMP scores, there may be value in investigating this relationship in other populations to determine if this factor is consistent across sports. Furthermore, the demands of training were significantly lower than the demands of

competition, so more research will be needed to assess what modifications to training increase intensity to the levels experienced in competition.

Since this study only measured the demands of female British university hockey, future studies will be required to quantify the demands of male British university hockey, allowing for comparisons between male and female hockey at this level. Finally, as this study was only performed on one hockey team, more studies will be needed to validate these results in other female British university hockey populations.

From a broader perspective, this research sets the foundation for future experimental studies to determine target training load threshold for hockey athletes. The relationships between training load and fitness outcomes examined in this study demonstrate which training load measures are most closely associated with fitness and fitness changes and are therefore best suited for developing target training loads. Future research studies will be needed to develop weekly training load thresholds to ensure that athletes are receiving the loads required to reach target fitness and performance outcomes, without risking overtraining. By adopting an experimental approach in which training load is monitored and individualized adjustments are made to ensure that athletes reach prescribed training doses, future studies could draw a causal relationship between training load and fitness measures, and target training load thresholds could be determined. Furthermore, in order to account for variation in the demands of the different playing positions, training dose could be individualized based on athletes' playing position, thereby ensuring that each athlete is best prepared for the demands that they will face in competition.

## Appendix A: Distance Covered in Speed Zones

Author(s)	Date	# subj	M/F	Level	Distance (m) in Speed Zones (km·h <sup>-1</sup> )						
Macutkiewicz & Sunderland	2011	25	F	I		<b>0-0.6</b>	<b>.7-6.0</b>	<b>6.1-11.0</b>	<b>11.1-15.0</b>	<b>15.1-19.0</b>	<b>&gt;19.0</b>
					Team	--	1653±547	1780±420	1226±249	620±172	232±96
Vescovi & Frayne	2015	68	F	N		0-8.0	8.1-16	16.1-20	20.1-32		
					Defense	2958±635	2926±696	551±188	113±83		
					Midfield	2657±777	3281±839	680±189	136±72		
					Forward	2379±637	2858±774	661±142	153±77		
Jennings et al (b)	2012	15	M	I		<b>0.4-17.0</b>	<b>&gt;17.0</b>				
					Defense	7686±400	1734±177				
					Midfield	7363±290	2554±134				
					Forward	7405±472	2189±456				
					Team	7441±511	2294±433				
Liu et al	2013	38	M	N		<b>&lt;7.6</b>	<b>7.6-11.1</b>	<b>11.2-15.5</b>	<b>15.6-20.1</b>	<b>20.1-29.1</b>	<b>&gt;29.1</b>
					Team	2580±261	1693±243	1434±321	1013±241	560±126	53±26
Jennings et al (a)	2012b	16	M	N		<b>0.4-17.0</b>	<b>&gt;17.0</b>				
					Team	6905±447	1652±416				
Sunderland & Edwards	2016	20	M	I		<b>15.5-20</b>	<b>&gt;20</b>				
					Defense	1364±82	438±59				
					Midfield	1589±212	443±52				
					Forward	1635±314	535±137				
Lythe	2008	18	M	I		<b>0-6.0</b>	<b>6.1-11.0</b>	<b>11.1-14.0</b>	<b>14.1-19.0</b>	<b>19.1-23.0</b>	<b>&gt;23.0</b>
					Team	2410±95	2585±258	1424±124	1232±263	355±110	124±69
Gabbett	2010	14	F	N		<b>0-3.6</b>	<b>3.7-10.8</b>	<b>10.9-18</b>	<b>18-25.2</b>	<b>&gt;25.2</b>	
					Defense	841±229	3618±821	1763±566	369±178	52±62	
					Midfield	681±243	3422±989	2181±558	571±244	77±69	
					Forward	728±231	3017±247	1941±198	423±195	46±57	
Vescovi	2016	44	F	I		<b>0-8.0</b>	<b>8.1-16.0</b>	<b>16.1-20</b>	<b>20.1-32.0</b>		
					Defense	2342±542	2287±440	405±81	101±35		
					Midfield	1799±542	2339±682	496±163	91±56		
					Forward	1241±355	1538±376	389±142	106±52		
Boran	2012	36	F	A		<b>0-13.0</b>	<b>13.1-15.1</b>	<b>15.2-19.4</b>	<b>19.5-20.5</b>	<b>20.5-21.6</b>	<b>&gt;21.6</b>
					Defense	825±242	2519±619	1138±308	852±343	478±164	50±41
					Midfield	736±134	2565±389	1358±215	1251±185	671±187	69±61
					Forward	789±118	2445±199	1077±530	893±311	645±159	141±84
McGuinness et al	2017	38	F	I		<b>0-7.9</b>	<b>8.0-15.9</b>	<b>16.0-19.9</b>	<b>&gt;20.0</b>		
					Defense	2432±400	2791±450	473±110	99±23		
					Midfield	1936±353	2944±378	675±105	135±21		
					Forward	1936±430	2792±456	612±170	141±39		
					Team	1982±394	2842±428	587±128	125±28		

I: International, N: National, A: Amateur

## **Appendix B: Participant Information Sheet**

### **Participant Information Sheet**

#### **A Comparison and Analysis of Internal and External Training Load Measures in Hockey Athletes**

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Thank you for your interest in this research study. This information sheet will describe exactly what participation in the study will require, the potential risks and benefits, how data will be used, and how to withdraw from the study. If you have any questions or would like further clarification, please do not hesitate to contact the principal investigator.

#### **Goals of this Study**

The goal of this study is to analyze various methods of measuring training load (ie how hard you are working) during hockey training and matches. Several different methods of measurement will be used: heart rate monitoring, global positioning system (GPS) monitoring, as well as a perceptual measure of how tired you feel, called rating of perceived exertion (RPE). Various equations for calculating training load from these measurements will be compared to help sports scientists better understand the relationships between these measures and which ones are most closely linked to changes in fitness. Training data will also be compared with match data to determine if training drills are performed at the same intensity as matches. Finally, match data from this study will be compared to other published hockey studies to examine how Durham University Hockey Club (DUHC) Women's 1<sup>st</sup> Team compares to other groups of hockey players.

#### **Participants**

This study will focus on outfield members of DUHC Women's 1<sup>st</sup> Team. You have been invited to participate in this study as you are a member of this group. No incentives will be provided for participation in this study.

#### **Study Details**

As a participant, you will be asked to take part in several testing procedures as well as to wear monitoring equipment during normal training and games. To be included in the study, interested participants will be required to give informed consent and complete a pre-screening questionnaire which will ask questions on current health status and existing injuries. Your height and weight will be measured and recorded so average height and weight of the study group can be determined.

#### *Measuring Resting Heart Rate*

As part of this study, your resting heart rate will be measured. You will be asked to lay face up in a quiet room for five minutes while wearing a heart rate strap across your chest.

#### *Treadmill Testing*

You will be asked to complete a treadmill test in the sports science laboratory twice, once at the beginning and once at the end of the study. You will likely find the treadmill test to be challenging; however, it is a submaximal test, meaning that it is designed to be completed

without you reaching exhaustion or working at maximum effort. Each session should be less than 45 minutes, and you will be asked to abstain from alcohol or any strenuous physical activity for 24 hours prior to testing. You will be required to complete a warmup before and cooldown after exercise. The test itself will consist of up to five sets of 4-minutes of running. The speed will start at  $7 \text{ km}\cdot\text{h}^{-1}$  and will increase by  $2 \text{ km}\cdot\text{h}^{-1}$  each stage up to a final speed of  $15 \text{ km}\cdot\text{h}^{-1}$ . There will be a 1-minute rest between each stage. You will wear a heart rate monitor across your chest for the duration of the test. Additionally, a small blood sample will be taken from your finger at the completion of each stage. Specifically, a sterilized needle will puncture your skin causing it to bleed slightly and a droplet of blood will be placed on a testing strip. This testing strip will then be placed in a device that will measure lactate (a substance which builds up in the blood during exercise).

### *30-15 Testing*

As part of this study, you will complete the 30-15 intermittent fitness test to help determine your maximum heart rate and fitness level. You will be required to warm up before testing and cooldown afterwards. The procedure for this test will be exactly the same as when you have completed it during normal fitness testing in the past; however, you will be asked to wear a heart rate strap during testing. Please note that this test will take place during a running session for the entire team – you will not need to do any additional 30-15 testing outside of normal training.

### *Training and Competition Monitoring*

Throughout the season, you will be asked to wear a heart rate monitor and GPS tracker during regularly scheduled training and competition. The heart rate monitor will be worn tightly across the chest, directly touching your skin, and the GPS unit will be placed in the pocket of a specially designed vest that can be worn under normal training attire or game kit. In addition to wearing the tracking devices, you will be asked to provide ratings from 0-10 on your perceived exertion during each session. These ratings will be collected via a google form which can be completed on your mobile phone or computer.

### **Risks and Benefits**

There are some risks of participating in the study that you should be aware of. Specifically, there is a risk of musculoskeletal injury; although proper warmup and cooldown techniques will be used to reduce the chance of injury. You are also at risk for cardiovascular complications due to the extra stress placed on this system during exercise; however, pre-screening will be undertaken prior to testing to help minimize the risk. Fainting, feeling nauseous, and/or vomiting is also possible, but if you ever begin to feel faint, the test will stop immediately. During the treadmill test, you will be at risk of falling off the treadmill, so a safety harness connected to an emergency stop will be used. Finally, as blood samples will be taken, there is a risk of cross contamination of blood or blood spillage; however, the proper university biohazard techniques and procedures will be followed to minimize these risks. Risk levels and steps taken to minimize risks can be found in the sports physiology lab risk assessment RA05.

Potential benefits of this study include the improvement of future hockey training at DUHC. Specifically, the training load measures being tested are designed to allow coaches to maximize performance and minimize overtraining and injury. Thus, measurements taken during the study can help DUHC, and other hockey programs who may read the results, improve training to better prepare their athletes for competition and decrease the risk of injury.



### **Anonymity/Confidentiality**

As a participant in this study, your data will be kept anonymous in any written reports of results. Specifically, if individual data is presented, you will be referred to by a number rather than by name (ie. participant 3). All data will be kept on a password protected computer. Additionally, anonymized, non-individualized data that has been averaged across participants that play similar positions (defense, midfield, forward), may be shared with DUHC coaching and strength and conditioning staff to enhance future training. When shared, the data will be sent in password protected files.

### **Data Use**

The data from this study will be used for the researcher's Masters by Research Thesis. It is possible that results may also be included in academic publications.

### **Withdrawing**

As a participant in this study, you are free to withdraw at any time, without providing a reason. If you chose to withdraw during the course of the study, you will have the choice as to whether the data previously collected from you can be included in study findings or should be destroyed. After the study is complete, you will have one week from the end of data collection to contact the principal investigator if you do not wish to have your data included in the results of the study. However, please note that even if you chose to withdraw, data collected up to that point may have already been shared with DUHC coaching staff as part of group averages for your playing position. If at any point you wish to withdraw from the study, please contact the principal investigator.

All protocols in this study are in accordance with the British Association of Sport and Exercise Sciences guidelines.<sup>1</sup>

*Thank you for taking the time to read through this Participant Information Sheet. Please do not hesitate to contact the principal investigator if you have any questions or would like clarification. Contact information has been provided at the beginning of this document. If you wish to discuss the study with the researcher's supervisors, their contact information has been provided at the beginning of this document. If you wish to discuss the study with the researcher's supervisors, their contact information has been provided as well.*

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<sup>1</sup> WINTER, E. M., JONES, A. M., DAVIDSON, R. C. R., BROMLEY, P. D. & MERCER, T. H. 2007. *Sport and Exercise Physiology Testing Guidelines: The British Association of Sport and Exercise Sciences Guide*, London ; New York, Routledge.

## Appendix C: Consent Form

### Consent Form

#### **A Comparison and Analysis of Internal and External Training Load Measures in Hockey Athletes**

Please circle **YES** or **NO** for each statement listed below:

1. I have read and fully understood the Participant Information Sheet and have been given the opportunity to ask any questions I may have about this study.  

**YES**                      **NO**
2. I am aware that this study follows the British Association of Sport and Exercise Science guidelines.  

**YES**                      **NO**
3. I consent to participate in the testing protocols – both the treadmill tests and the 30-15 fitness test.  

**YES**                      **NO**
4. I give my permission for my heart rate and location to be tracked in hockey trainings and competition.  

**YES**                      **NO**
5. I am aware that my participation in this study is completely voluntary and that I may withdraw from this study at any time, without giving a reason.  

**YES**                      **NO**
6. I consent to my personal data being stored on a password protected computer and in password protected documents.  

**YES**                      **NO**
7. I consent that my anonymized data may be shared with the Durham University Hockey Club's Strength and Conditioning and Hockey Coaches.  

**YES**                      **NO**
8. I consent to my anonymized data from this study being published as part of a Master's thesis and potentially in other academic publications.  

**YES**                      **NO**

After reading the participant information sheet and consent form, I confirm that my consent is freely given, and I agree to take part in this study.

Signature: \_\_\_\_\_ (Participant)

Signature: \_\_\_\_\_ (Researcher)

Date: \_\_\_\_\_

## Appendix D: Prescreening Questionnaire

### **Prescreening Questionnaire**

*Adapted Physical Activities Readiness Questionnaire (PAR-Q)<sup>2</sup>*

Name: \_\_\_\_\_ Date: \_\_\_\_\_

Please circle **YES** or **NO** for each question below

- |  |            |           |
|--|------------|-----------|
| 1. Has your doctor ever said that you have heart trouble?  | <b>YES</b> | <b>NO</b> |
| 2. Do you frequently have pains in your heart and chest?   | <b>YES</b> | <b>NO</b> |
| 3. Do you often feel faint or have spells of severe dizziness?   | <b>YES</b> | <b>NO</b> |
| 4. Has your doctor said that your blood pressure is too high?  | <b>YES</b> | <b>NO</b> |
| 5. Has your doctor ever told you that you have a chronic bone or joint condition and should avoid high levels of activity? | <b>YES</b> | <b>NO</b> |
| 6. Do you have any existing injuries?  | <b>YES</b> | <b>NO</b> |
| If so, have you been cleared for regular activity by a physiotherapist or doctor?  |            |           |
|  | <b>YES</b> | <b>NO</b> |
| 7. Do you know of any good reason why you should not perform intense physical activity?                                    | <b>YES</b> | <b>NO</b> |

If you answered yes to any of the questions above, please explain below.

---

---

---

<sup>2</sup> Adapted from the Physical Fitness Readiness Questionnaire as outlined by Humphrey and Lakomy (2003).

## Appendix E: Python Code for Training Sessions

```
input_wb="File_name.xlsx"
output='File_name.xlsx'

PM="Yes"
#####

import openpyxl
import math
import datetime

wb = openpyxl.load_workbook(input_wb)
wbvalues=openpyxl.load_workbook('Mastervalues.xlsx')
wboutput=openpyxl.Workbook()
soutput=wboutput.active
s1=wb["P"]
svalues=wbvalues.active
speriods=wb["C"]
sRPEs=wb["R"]

def blankrow(col, sheet, st):
    for i in range(st, sheet.max_row+2):
        if sheet.cell(row=i, column=col).value==None:
            return i
            break

def minutes(t):
    h=t.hour
    m=t.minute
    s=t.second
    return h*60+m+s/60

def add12(t):
    h=t.hour
    m=t.minute
    s=t.second
    return datetime.time(h+12, m, s)

def addnone(t):
    h=t.hour
    m=t.minute
    s=t.second
    return datetime.time(h, m, s)

MaxHR=(Sell and Ledesma, 2016)
for i in range(2, blankrow(2,svalues,2)):
    MaxHR[svalues.cell(row=i, column=1).value]=svalues.cell(row=i, column=2).value

MinHR={}
for i in range(2, blankrow(2,svalues,2)):
    MinHR[svalues.cell(row=i, column=1).value]=svalues.cell(row=i, column=3).value

aValue={}
for i in range(2, blankrow(2,svalues,2)):
    aValue[svalues.cell(row=i, column=1).value]=svalues.cell(row=i, column=4).value
```

```

bValue={}
for i in range(2, blankrow(2,svalues,2)):
    bValue[svalues.cell(row=i, column=1).value]=svalues.cell(row=i, column=5).value

kValue={}
for i in range(2, blankrow(2,svalues,2)):
    kValue[svalues.cell(row=i, column=1).value]=svalues.cell(row=i, column=6).value

if PM=="Yes":
    for i in range (1, s1.max_column+1, 3):
        for u in range (4, blankrow(i, s1, 4)):
            s1.cell(row=u, column=i).value=add12(s1.cell(row=u, column=i).value)
else:
    for i in range (1, s1.max_column+1, 3):
        for u in range (4, blankrow(i, s1, 4)):
            s1.cell(row=u, column=i).value=addnone(s1.cell(row=u, column=i).value)

p={}
for i in range (1, s1.max_column, 3):
    n=s1.cell(row=2, column=i).value
    l=[]
    for u in range (2, blankrow(1, speriods, 2)):
        if speriods.cell(row=u, column=1).value==n:
            if speriods.cell(row=u, column=2).value!="Session":
                if speriods.cell(row=u, column=2).value[-1]==kValue[n]:
                    l.append(datetime.datetime.strptime(speriods.cell(row=u,
column=5).value, "%I:%M:%S %p").time())
                    l.append(datetime.datetime.strptime(speriods.cell(row=u,
column=6).value, "%I:%M:%S %p").time())
    p[n]=l

#####

session_period=[]
for u in range (4, blankrow(1, speriods,2)):
    if speriods.cell(row=u, column=2).value=="Sx":
        session_period.append(datetime.datetime.strptime(speriods.cell(row=u, column=5).value,
"%I:%M:%S %p").time())
        session_period.append(datetime.datetime.strptime(speriods.cell(row=u, column=6).value,
"%I:%M:%S %p").time())
    break

wboutput.create_sheet('Sx')
sSx=wboutput['Sx']

headings=["Name", "Minutes", "Position", "sTRIMP", "nTRIMP", "iTRIMP", "% Max HR", "TD", "Workrate",
"Zone 1", "Zone 2", "Zone 3", "Zone 4", "Zone 5", "Zone 6", "Zone 7", "Effindex 1", "Effindex 2"]
for u in range(0,18):
    sSx.cell(row=1, column=u+1).value=headings[u]

for i in range (1, s1.max_column+1, 3):
    for u in range (4, blankrow(i, s1, 4)):
        if s1.cell(row=u, column=i).value<session_period[0] or s1.cell(row=u, column=i).value>
session_period[1]:
            s1.cell(row=u, column=i+1).value=0

y6=2
for i in range (2, s1.max_column+1, 3):
    x24=0

```

```

Max=MaxHR[s1.cell(row=2, column=i-1).value]
Min=MinHR[s1.cell(row=2, column=i-1).value]
a=aValue[s1.cell(row=2, column=i-1).value]
b=bValue[s1.cell(row=2, column=i-1).value]
sSx.cell(row=y6, column=1).value= s1.cell(row=2, column=i-1).value
if a!="--":
    for u in range (4, blankrow(i,s1,4)):
        HRR=(s1.cell(row=u, column=i).value-Min)/(Max-Min)
        if 1.02>HRR>0:
            x24+=HRR*a*math.exp(b*HRR)
        sSx.cell(row=y6, column=6).value=x24/60
    else:
        sSx.cell(row=y6, column=6).value="--"
y6+=1

for i in range (2, s1.max_column+1, 3):
    HR=MaxHR[s1.cell(row=2, column=i-1).value]
    for u in range (4, blankrow(i,s1,4)):
        s1.cell(row=u, column=i+1).value= s1.cell(row=u, column=i).value/HR

y5=2
for i in range (2, s1.max_column+1, 3):
    x50=0
    for u in range (4, blankrow(i, s1, 4)):
        if 0.715>s1.cell(row=u, column=i+1).value>=0.645:
            x50+=1.25
        elif 0.785>s1.cell(row=u, column=i+1).value>=0.715:
            x50+=1.71
        elif .855>s1.cell(row=u, column=i+1).value>=0.785:
            x50+=2.54
        elif .925>s1.cell(row=u, column=i+1).value>=.855:
            x50+=3.61
        elif 1.02>s1.cell(row=u, column=i+1).value>=.925:
            x50+=5.16
    sSx.cell(row=y5, column=4).value=x50/60
y5+=1

y7=2
for i in range (2, s1.max_column+1, 3):
    x70=0
    for u in range (4, blankrow(i, s1, 4)):
        if 0.67>s1.cell(row=u, column=i+1).value>=0.59:
            x70+=0.91
        elif 0.75>s1.cell(row=u, column=i+1).value>=0.67:
            x70+=1.49
        elif .83>s1.cell(row=u, column=i+1).value>=0.75:
            x70+=2.44
        elif .91>s1.cell(row=u, column=i+1).value>=.83:
            x70+=3.99
        elif 1.02>s1.cell(row=u, column=i+1).value>=.91:
            x70+=6.74
    sSx.cell(row=y7, column=5).value=x70/60
y7+=1

g1=2
for i in range (2, s1.max_column+1, 3):
    m2=c2=0
    for u in range (4, blankrow(i, s1, 4)):
        if s1.cell(row=u, column=i+1).value!=0:
            m2+=s1.cell(row=u, column=i+1).value

```

```

        c2+=1
    if c2==0:
        sSx.cell(row=g1, column=7).value="--"
    else:
        sSx.cell(row=g1, column=7).value=m2/c2
    g1+=1

for u in range (2, blankrow(1,sSx,2)):
    for i in range (2, blankrow(1, speriods,2)):
        if speriods.cell(row=i, column=2).value=="Sx":
            if sSx.cell(row=u, column=1).value==speriods.cell(row=i, column=1).value:
                sSx.cell(row=u,
column=2).value=minutes(datetime.datetime.strptime("0"+speriods.cell(row=i, column=8).value,
"%H:%M:%S").time())
                sSx.cell(row=u, column=8).value=speriods.cell(row=i, column=10).value
                sSx.cell(row=u, column=10).value=speriods.cell(row=i, column=12).value
                sSx.cell(row=u, column=11).value=speriods.cell(row=i, column=13).value
                sSx.cell(row=u, column=12).value=speriods.cell(row=i, column=14).value
                sSx.cell(row=u, column=13).value=speriods.cell(row=i, column=15).value
                sSx.cell(row=u, column=14).value=speriods.cell(row=i, column=16).value
                sSx.cell(row=u, column=15).value=speriods.cell(row=i, column=17).value

for u in range (2, blankrow(1,sSx,2)):
    if sSx.cell(row=u, column=2).value!=0 and sSx.cell(row=u, column=2).value!=None:
        sSx.cell(row=u, column=9).value=sSx.cell(row=u, column=8).value/sSx.cell(row=u,
column=2).value
    else:
        sSx.cell(row=u, column=9).value="--"
    if sSx.cell(row=u, column=14).value!=None and sSx.cell(row=u, column=15).value!=None:
        sSx.cell(row=u, column=16).value=sSx.cell(row=u, column=14).value+sSx.cell(row=u,
column=15).value
    else:
        sSx.cell(row=u, column=16).value="--"
    if sSx.cell(row=u, column=7).value!=0 and sSx.cell(row=u, column=7).value!=None and
sSx.cell(row=u, column=7).value!="--" and sSx.cell(row=u, column=9).value!=0 and sSx.cell(row=u,
column=9).value!=None and sSx.cell(row=u, column=9).value!="--":
        sSx.cell(row=u, column=18).value=sSx.cell(row=u, column=9).value/sSx.cell(row=u,
column=7).value
    else:
        sSx.cell(row=u, column=18).value="--"
    if sSx.cell(row=u, column=8).value!=0 and sSx.cell(row=u, column=8).value!=None and
sSx.cell(row=u, column=6).value!=0 and sSx.cell(row=u, column=6).value!=None and sSx.cell(row=u,
column=6).value!="--" and sSx.cell(row=u, column=8).value!="--":
        sSx.cell(row=u, column=17).value=sSx.cell(row=u, column=8).value/sSx.cell(row=u,
column=6).value
    else:
        sSx.cell(row=u, column=17).value="--"

#####

for i in range (1, s1.max_column, 3):
    n=s1.cell(row=2, column=i).value
    if p[n]==[]:
        print(n+ " no phases")
    else:
        for u in range (4, blankrow(i, s1, 4)):
            x=p[n]
            if s1.cell(row=u, column=i).value< x[0] or s1.cell(row=u, column=i).value> x[len(x)-
1]:
                #len(x)-1 because its starts counting at 0

```

```

        s1.cell(row=u, column=i+1).value=0
    else:
        for o in range (1, len(x),2):
            if x[o]<s1.cell(row=u, column=i).value<x[o+1]:
                s1.cell(row=u, column=i+1).value=0

#iTRIMP (before change to %maxHR)
y2=2
for i in range (2, s1.max_column+1, 3):
    x2=0
    Max=MaxHR[s1.cell(row=2, column=i-1).value]
    Min=MinHR[s1.cell(row=2, column=i-1).value]
    a=aValue[s1.cell(row=2, column=i-1).value]
    b=bValue[s1.cell(row=2, column=i-1).value]
    if a!="--":
        for u in range (4, blankrow(i,s1,4)):
            HRR=(s1.cell(row=u, column=i).value-Min)/(Max-Min)
            if 1.02>HRR>0:
                x2=x2+HRR*a*math.exp(b*HRR)
        soutput.cell(row=y2, column=9).value=x2/60
    else:
        soutput.cell(row=y2, column=9).value="--"
    y2+=1

#Changes to %max HR
for i in range (2, s1.max_column+1, 3):
    HR=MaxHR[s1.cell(row=2, column=i-1).value]
    for u in range (4, blankrow(i,s1,4)):
        s1.cell(row=u, column=i).value= s1.cell(row=u, column=i).value/HR

#Stagno TRIMP
y1=2
for i in range (2, s1.max_column+1, 3):
    x1=0
    for u in range (4, blankrow(i, s1, 4)):
        if 0.715>s1.cell(row=u, column=i).value>=0.645:
            x1=x1+1.25
        elif 0.785>s1.cell(row=u, column=i).value>=0.715:
            x1=x1+1.71
        elif .855>s1.cell(row=u, column=i).value>=0.785:
            x1=x1+2.54
        elif .925>s1.cell(row=u, column=i).value>=.855:
            x1=x1+3.61
        elif 1.02>s1.cell(row=u, column=i).value>=.925:
            x1=x1+5.16
    soutput.cell(row=y1, column=1).value= s1.cell(row=2, column=i-1).value
    soutput.cell(row=y1, column=7).value=x1/60
    y1+=1

#FTRIMP
y3=2
for i in range (2, s1.max_column+1, 3):
    x3=0
    for u in range (4, blankrow(i, s1, 4)):
        if 0.67>s1.cell(row=u, column=i).value>=0.59:
            x3=x3+0.91
        elif 0.75>s1.cell(row=u, column=i).value>=0.67:
            x3=x3+1.49

```



```

        elif .83>s1.cell(row=u, column=i).value>=0.75:
            x3=x3+2.44
        elif .91>s1.cell(row=u, column=i).value>=.83:
            x3=x3+3.99
        elif 1.02>s1.cell(row=u, column=i).value>=.91:
            x3=x3+6.74
    soutput.cell(row=y3, column=8).value=x3/60
    y3+=1

#Percent Max HR
y4=2
for i in range (2, s1.max_column+1, 3):
    m=0
    c=0
    for u in range (4, blankrow(i, s1, 4)):
        if s1.cell(row=u, column=i).value!=0:
            m+=s1.cell(row=u, column=i).value
            c+=1
    if c==0:
        soutput.cell(row=y4, column=10).value="--"
    else:
        soutput.cell(row=y4, column=10).value=m/c
    y4+=1

#Importing GPS
TD={}
M={}
Z1={}
Z2={}
Z3={}
Z4={}
Z5={}
Z6={}

for u in range (1, blankrow(1,soutput,2)):
    TD[soutput.cell(row=u, column=1).value]=M[soutput.cell(row=u,
column=1).value]=Z1[soutput.cell(row=u, column=1).value]=Z2[soutput.cell(row=u,
column=1).value]=Z3[soutput.cell(row=u, column=1).value]=Z4[soutput.cell(row=u,
column=1).value]=Z5[soutput.cell(row=u, column=1).value]=Z6[soutput.cell(row=u, column=1).value]=0
    for i in range (2, blankrow(1, speriods,2)):
        if soutput.cell(row=u, column=1).value==speriods.cell(row=i, column=1).value:
            if speriods.cell(row=i, column=2).value!="Session":
                if speriods.cell(row=i, column=2).value[-1]==kValue[speriods.cell(row=i,
column=1).value]:
                    TD[soutput.cell(row=u, column=1).value]+=speriods.cell(row=i,
column=10).value
                    M[soutput.cell(row=u,
column=1).value]+=minutes(datetime.datetime.strptime("0"+speriods.cell(row=i, column=8).value,
"%H:%M:%S").time())
                    Z1[soutput.cell(row=u, column=1).value]+=speriods.cell(row=i,
column=12).value
                    Z2[soutput.cell(row=u, column=1).value]+=speriods.cell(row=i,
column=13).value
                    Z3[soutput.cell(row=u, column=1).value]+=speriods.cell(row=i,
column=14).value
                    Z4[soutput.cell(row=u, column=1).value]+=speriods.cell(row=i,
column=15).value
                    Z5[soutput.cell(row=u, column=1).value]+=speriods.cell(row=i,
column=16).value

```

```

        Z6[soutput.cell(row=u, column=1).value]+=speriods.cell(row=i,
column=17).value
        soutput.cell(row=u, column=2).value=M[soutput.cell(row=u, column=1).value]
        soutput.cell(row=u, column=11).value=TD[soutput.cell(row=u, column=1).value]
        soutput.cell(row=u, column=13).value=Z1[soutput.cell(row=u, column=1).value]
        soutput.cell(row=u, column=14).value=Z2[soutput.cell(row=u, column=1).value]
        soutput.cell(row=u, column=15).value=Z3[soutput.cell(row=u, column=1).value]
        soutput.cell(row=u, column=16).value=Z4[soutput.cell(row=u, column=1).value]
        soutput.cell(row=u, column=17).value=Z5[soutput.cell(row=u, column=1).value]
        soutput.cell(row=u, column=18).value=Z6[soutput.cell(row=u, column=1).value]
        if M[soutput.cell(row=u, column=1).value]!=0:
            soutput.cell(row=u, column=12).value=TD[soutput.cell(row=u,
column=1).value]/M[soutput.cell(row=u, column=1).value]
        else:
            soutput.cell(row=u, column=12).value="--"
'''
for u in range(2, blankrow(2, speriods, 2)):
    if speriods.cell(row=u, column=2).value=="Session":
        for i in range (1, blankrow(1, soutput, 2)):
            if speriods.cell(row=u, column=1).value==soutput.cell(row=i, column=1).value:
                soutput.cell(row=i,
column=2).value=minutes(datetime.strptime("0"+speriods.cell(row=u, column=8).value,
"%H:%M:%S").time())
                soutput.cell(row=i, column=11).value=speriods.cell(row=u,
column=10).value
                soutput.cell(row=i, column=12).value=speriods.cell(row=u,
column=11).value
                soutput.cell(row=i, column=13).value=speriods.cell(row=u,
column=12).value
                soutput.cell(row=i, column=14).value=speriods.cell(row=u,
column=13).value
                soutput.cell(row=i, column=15).value=speriods.cell(row=u,
column=14).value
                soutput.cell(row=i, column=16).value=speriods.cell(row=u,
column=15).value
                soutput.cell(row=i, column=17).value=speriods.cell(row=u,
column=16).value
                soutput.cell(row=i, column=18).value=speriods.cell(row=u,
column=17).value
'''
#RPE
for u in range(1, blankrow(2, sRPEs, 1)):
    for i in range (1, blankrow(1, soutput, 2)):
        if sRPEs.cell(row=u, column=1).value==soutput.cell(row=i, column=1).value:
            if soutput.cell(row=i, column=2).value==None or soutput.cell(row=i,
column=2).value==0:
                soutput.cell(row=i, column =3).value=soutput.cell(row=i,
column=4).value = soutput.cell(row=i, column=5).value= soutput.cell(row=i, column=6).value="--"
            else:
                soutput.cell(row=i, column=3).value=sRPEs.cell(row=u,
column=2).value * soutput.cell(row=i, column=2).value/10
                soutput.cell(row=i, column=4).value=sRPEs.cell(row=u,
column=3).value * soutput.cell(row=i, column=2).value/10
                soutput.cell(row=i, column=5).value=sRPEs.cell(row=u,
column=4).value * soutput.cell(row=i, column=2).value/10
                soutput.cell(row=i, column=6).value=sRPEs.cell(row=u,
column=5).value * soutput.cell(row=i, column=2).value/10

#Zone 7 and effindex
for u in range (2, blankrow(1, soutput, 2)):

```

```

        if soutput.cell(row=u, column=17).value==None or soutput.cell(row=u, column=18).value==None:
            soutput.cell(row=u, column=19).value="--"
        else:
            soutput.cell(row=u, column=19).value=soutput.cell(row=u,
column=17).value+soutput.cell(row=u, column=18).value
            if soutput.cell(row=u, column=11).value==None or soutput.cell(row=u, column=9).value==None or
soutput.cell(row=u, column=9).value==0 or soutput.cell(row=u, column=9).value=="--":
                soutput.cell(row=u, column=20).value="--"
            else:
                soutput.cell(row=u, column=20).value=soutput.cell(row=u,
column=11).value/soutput.cell(row=u, column=9).value
                if soutput.cell(row=u, column=12).value==None or soutput.cell(row=u, column=10).value==None or
soutput.cell(row=u, column=10).value==0 or soutput.cell(row=u, column=10).value=="--" or
soutput.cell(row=u, column=12).value=="--":
                    soutput.cell(row=u, column=21).value="--"
                else:
                    soutput.cell(row=u, column=21).value=soutput.cell(row=u,
column=12).value/soutput.cell(row=u, column=10).value

headings=["Name", "Minutes", "rRPE", "uRPE", "lRPE", "oRPE", "sTRIMP", "nTRIMP", "iTRIMP", "% Max
HR", "TD", "Workrate", "Zone 1", "Zone 2", "Zone 3", "Zone 4", "Zone 5", "Zone 6", "Zone 7", "Effindex 1",
"Effindex 2"]
for u in range(0,21):
    soutput.cell(row=1, column=u+1).value=headings[u]

wboutput.save(output)

```

## Appendix F: Python Code for Matches

```
input_wb="File_name.xlsx"
output='File_name.xlsx'

import datetime
halftime=datetime.time(00, 00, 00)
PM="Yes"

#####

import openpyxl
import math

wb = openpyxl.load_workbook(input_wb)
wbvalues=openpyxl.load_workbook('Mastervalues.xlsx')
wboutput=openpyxl.Workbook()
soutput=wboutput.active
s1=wb["P"]
svalues=wbvalues.active
speriods=wb["C"]
sRPEs=wb["R"]

def blankrow(col, sheet, st):
    for i in range (st, sheet.max_row+2):
        if sheet.cell(row=i, column=col).value==None:
            return i
            break

def minutes(t):
    h=t.hour
    m=t.minute
    s=t.second
    return h*60+m+s/60

def add12(t):
    h=t.hour
    m=t.minute
    s=t.second
    if h<11:
        return datetime.time(h+12, m, s)
    else:
        return datetime.time(h,m,s)

def addnone(t):
    h=t.hour
    m=t.minute
    s=t.second
    return datetime.time(h, m, s)

MaxHR={}
for i in range(2, blankrow(2,svalues,2)):
    MaxHR[svalues.cell(row=i, column=1).value]=svalues.cell(row=i, column=2).value

MinHR={}
for i in range(2, blankrow(2,svalues,2)):
    MinHR[svalues.cell(row=i, column=1).value]=svalues.cell(row=i, column=3).value
```

```

aValue={}
for i in range(2, blankrow(2,svalues,2)):
    aValue[svalues.cell(row=i, column=1).value]=svalues.cell(row=i, column=4).value

bValue={}
for i in range(2, blankrow(2,svalues,2)):
    bValue[svalues.cell(row=i, column=1).value]=svalues.cell(row=i, column=5).value

kValue={}
for i in range(2, blankrow(2,svalues,2)):
    kValue[svalues.cell(row=i, column=1).value]=svalues.cell(row=i, column=6).value

if PM=="Yes":
    for i in range (1, s1.max_column+1, 3):
        for u in range (4, blankrow(i, s1, 4)):
            s1.cell(row=u, column=i).value=add12(s1.cell(row=u, column=i).value)
else:
    for i in range (1, s1.max_column+1, 3):
        for u in range (4, blankrow(i, s1, 4)):
            s1.cell(row=u, column=i).value=addnone(s1.cell(row=u, column=i).value)

p={}
for i in range (1, s1.max_column, 3):
    n=s1.cell(row=2, column=i).value
    l=[]
    for u in range (2, blankrow(1, speriods, 2)):
        if speriods.cell(row=u, column=1).value==n:
            if speriods.cell(row=u, column=2).value!="Session":
                if speriods.cell(row=u, column=2).value[-1]==kValue[n]:
                    l.append(datetime.datetime.strptime(speriods.cell(row=u,
column=5).value, "%I:%M:%S %p").time())
                    l.append(datetime.datetime.strptime(speriods.cell(row=u,
column=6).value, "%I:%M:%S %p").time())
                p[n]=l
#####
game_period=[]
for u in range (4, blankrow(1, speriods,2)):
    if speriods.cell(row=u, column=2).value=="Gx":
        game_period.append(datetime.datetime.strptime(speriods.cell(row=u, column=5).value,
"%I:%M:%S %p").time())
        game_period.append(datetime.datetime.strptime(speriods.cell(row=u, column=6).value,
"%I:%M:%S %p").time())
        break

session_period=[]
for u in range (4, blankrow(1, speriods,2)):
    if speriods.cell(row=u, column=2).value=="Sx":
        session_period.append(datetime.datetime.strptime(speriods.cell(row=u, column=5).value,
"%I:%M:%S %p").time())
        session_period.append(datetime.datetime.strptime(speriods.cell(row=u, column=6).value,
"%I:%M:%S %p").time())
        break

wboutput.create_sheet('Gx')
sGx=wboutput['Gx']
wboutput.create_sheet('Sx')
sSx=wboutput['Sx']

headings=["Name", "Minutes", "Position", "sTRIMP", "nTRIMP", "iTRIMP", "% Max HR", "TD", "Workrate",
"Zone 1", "Zone 2", "Zone 3", "Zone 4", "Zone 5", "Zone 6", "Zone 7", "Effindex 1", "Effindex 2"]

```

```

for u in range(0,18):
    sGx.cell(row=1, column=u+1).value=headings[u]
    sSx.cell(row=1, column=u+1).value=headings[u]

for i in range (1, s1.max_column+1, 3):
    for u in range (4, blankrow(i, s1, 4)):
        if s1.cell(row=u, column=i).value<session_period[0] or s1.cell(row=u, column=i).value>
session_period[1]:
            s1.cell(row=u, column=i+1).value=0

y6=2
for i in range (2, s1.max_column+1, 3):
    x24=0
    Max=MaxHR[s1.cell(row=2, column=i-1).value]
    Min=MinHR[s1.cell(row=2, column=i-1).value]
    a=aValue[s1.cell(row=2, column=i-1).value]
    b=bValue[s1.cell(row=2, column=i-1).value]
    sSx.cell(row=y6, column=1).value= s1.cell(row=2, column=i-1).value
    if a!="--":
        for u in range (4, blankrow(i,s1,4)):
            HRR=(s1.cell(row=u, column=i).value-Min)/(Max-Min)
            if 1.02>HRR>0:
                x24+=HRR*a*math.exp(b*HRR)
            sSx.cell(row=y6, column=6).value=x24/60
        else:
            sSx.cell(row=y6, column=6).value="--"
    y6+=1

for i in range (2, s1.max_column+1, 3):
    HR=MaxHR[s1.cell(row=2, column=i-1).value]
    for u in range (4, blankrow(i,s1,4)):
        s1.cell(row=u, column=i+1).value= s1.cell(row=u, column=i).value/HR

y5=2
for i in range (2, s1.max_column+1, 3):
    x50=0
    for u in range (4, blankrow(i, s1, 4)):
        if 0.715>s1.cell(row=u, column=i+1).value>=0.645:
            x50+=1.25
        elif 0.785>s1.cell(row=u, column=i+1).value>=0.715:
            x50+=1.71
        elif .855>s1.cell(row=u, column=i+1).value>=0.785:
            x50+=2.54
        elif .925>s1.cell(row=u, column=i+1).value>=.855:
            x50+=3.61
        elif 1.02>s1.cell(row=u, column=i+1).value>=.925:
            x50+=5.16
    sSx.cell(row=y5, column=4).value=x50/60
    y5+=1

y7=2
for i in range (2, s1.max_column+1, 3):
    x70=0
    for u in range (4, blankrow(i, s1, 4)):
        if 0.67>s1.cell(row=u, column=i+1).value>=0.59:
            x70+=0.91
        elif 0.75>s1.cell(row=u, column=i+1).value>=0.67:
            x70+=1.49
        elif .83>s1.cell(row=u, column=i+1).value>=0.75:
            x70+=2.44

```

```

        elif .91>s1.cell(row=u, column=i+1).value>=.83:
            x70+=3.99
        elif 1.02>s1.cell(row=u, column=i+1).value>=.91:
            x70+=6.74
    sSx.cell(row=y7, column=5).value=x70/60
    y7+=1

g1=2
for i in range (2, s1.max_column+1, 3):
    m2=c2=0
    for u in range (4, blankrow(i, s1, 4)):
        if s1.cell(row=u, column=i+1).value!=0:
            m2+=s1.cell(row=u, column=i+1).value
            c2+=1
    if c2==0:
        sSx.cell(row=g1, column=7).value="--"
    else:
        sSx.cell(row=g1, column=7).value=m2/c2
    g1+=1

for u in range (2, blankrow(1,sSx,2)):
    for i in range (2, blankrow(1, speriods,2)):
        if speriods.cell(row=i, column=2).value=="Sx":
            if sSx.cell(row=u, column=1).value==speriods.cell(row=i, column=1).value:
                sSx.cell(row=u,
column=2).value=minutes(datetime.datetime.strptime("0"+speriods.cell(row=i, column=8).value,
"%H:%M:%S").time())
                sSx.cell(row=u, column=8).value=speriods.cell(row=i, column=10).value
                sSx.cell(row=u, column=10).value=speriods.cell(row=i, column=12).value
                sSx.cell(row=u, column=11).value=speriods.cell(row=i, column=13).value
                sSx.cell(row=u, column=12).value=speriods.cell(row=i, column=14).value
                sSx.cell(row=u, column=13).value=speriods.cell(row=i, column=15).value
                sSx.cell(row=u, column=14).value=speriods.cell(row=i, column=16).value
                sSx.cell(row=u, column=15).value=speriods.cell(row=i, column=17).value

for u in range (2, blankrow(1,sSx,2)):
    if sSx.cell(row=u, column=2).value!=0 and sSx.cell(row=u, column=2).value!=None:
        sSx.cell(row=u, column=9).value=sSx.cell(row=u, column=8).value/sSx.cell(row=u,
column=2).value
    else:
        sSx.cell(row=u, column=9).value="--"
    if sSx.cell(row=u, column=14).value!=None and sSx.cell(row=u, column=15).value!=None:
        sSx.cell(row=u, column=16).value=sSx.cell(row=u, column=14).value+sSx.cell(row=u,
column=15).value
    else:
        sSx.cell(row=u, column=16).value="--"
    if sSx.cell(row=u, column=7).value!=0 and sSx.cell(row=u, column=7).value!=None and
sSx.cell(row=u, column=7).value!="--" and sSx.cell(row=u, column=9).value!=0 and sSx.cell(row=u,
column=9).value!=None and sSx.cell(row=u, column=9).value!="--":
        sSx.cell(row=u, column=18).value=sSx.cell(row=u, column=9).value/sSx.cell(row=u,
column=7).value
    else:
        sSx.cell(row=u, column=18).value="--"
    if sSx.cell(row=u, column=8).value!=0 and sSx.cell(row=u, column=8).value!=None and
sSx.cell(row=u, column=6).value!=0 and sSx.cell(row=u, column=6).value!=None and sSx.cell(row=u,
column=6).value!="--" and sSx.cell(row=u, column=8).value!="--":
        sSx.cell(row=u, column=17).value=sSx.cell(row=u, column=8).value/sSx.cell(row=u,
column=6).value
    else:
        sSx.cell(row=u, column=17).value="--"

```

###

```
for i in range (1, s1.max_column+1, 3):
    for u in range (4, blankrow(i, s1, 4)):
        if s1.cell(row=u, column=i).value<game_period[0] or s1.cell(row=u, column=i).value>
game_period[1]:
            s1.cell(row=u, column=i+1).value=0
            s1.cell(row=u, column=i+2).value=0
```

y4=2

```
for i in range (2, s1.max_column+1, 3):
    x25=0
    Max=MaxHR[s1.cell(row=2, column=i-1).value]
    Min=MinHR[s1.cell(row=2, column=i-1).value]
    a=aValue[s1.cell(row=2, column=i-1).value]
    b=bValue[s1.cell(row=2, column=i-1).value]
    sGx.cell(row=y4, column=1).value= s1.cell(row=2, column=i-1).value
    if a!="--":
        for u in range (4, blankrow(i,s1,4)):
            HRR=(s1.cell(row=u, column=i).value-Min)/(Max-Min)
            if 1.02>HRR>0:
                x25+=HRR*a*math.exp(b*HRR)
            sGx.cell(row=y4, column=6).value=x25/60
        else:
            sGx.cell(row=y4, column=6).value="--"
    y4+=1
```

y8=2

```
for i in range (2, s1.max_column+1, 3):
    x80=0
    for u in range (4, blankrow(i, s1, 4)):
        if 0.715>s1.cell(row=u, column=i+1).value>=0.645:
            x80+=1.25
        elif 0.785>s1.cell(row=u, column=i+1).value>=0.715:
            x80+=1.71
        elif .855>s1.cell(row=u, column=i+1).value>=0.785:
            x80+=2.54
        elif .925>s1.cell(row=u, column=i+1).value>=.855:
            x80+=3.61
        elif 1.02>s1.cell(row=u, column=i+1).value>=.925:
            x80+=5.16
    sGx.cell(row=y8, column=4).value=x80/60
    y8+=1
```

y9=2

```
for i in range (2, s1.max_column+1, 3):
    x90=0
    for u in range (4, blankrow(i, s1, 4)):
        if 0.67>s1.cell(row=u, column=i+1).value>=0.59:
            x90+=0.91
        elif 0.75>s1.cell(row=u, column=i+1).value>=0.67:
            x90+=1.49
        elif .83>s1.cell(row=u, column=i+1).value>=0.75:
            x90+=2.44
        elif .91>s1.cell(row=u, column=i+1).value>=.83:
            x90+=3.99
        elif 1.02>s1.cell(row=u, column=i+1).value>=.91:
            x90+=6.74
```



```

sGx.cell(row=y9, column=5).value=x90/60
y9+=1

g2=2
for i in range (2, s1.max_column+1, 3):
    m3=c3=0
    for u in range (4, blankrow(i, s1, 4)):
        if s1.cell(row=u, column=i+1).value!=0:
            m3+=s1.cell(row=u, column=i+1).value
            c3+=1
    if c3==0:
        sGx.cell(row=g2, column=7).value="--"
    else:
        sGx.cell(row=g2, column=7).value=m3/c3
    g2+=1

for u in range (2, blankrow(1,sGx,2)):
    for i in range (2, blankrow(1, speriods,2)):
        if speriods.cell(row=i, column=2).value=="Gx":
            if sGx.cell(row=u, column=1).value==speriods.cell(row=i, column=1).value:
                sGx.cell(row=u,
column=2).value=minutes(datetime.datetime.strptime("0"+speriods.cell(row=i, column=8).value,
"%H:%M:%S").time())
                sGx.cell(row=u, column=8).value=speriods.cell(row=i, column=10).value
                sGx.cell(row=u, column=10).value=speriods.cell(row=i, column=12).value
                sGx.cell(row=u, column=11).value=speriods.cell(row=i, column=13).value
                sGx.cell(row=u, column=12).value=speriods.cell(row=i, column=14).value
                sGx.cell(row=u, column=13).value=speriods.cell(row=i, column=15).value
                sGx.cell(row=u, column=14).value=speriods.cell(row=i, column=16).value
                sGx.cell(row=u, column=15).value=speriods.cell(row=i, column=17).value

for u in range (2, blankrow(1,sGx,2)):
    if sGx.cell(row=u, column=2).value!=0 and sGx.cell(row=u, column=2).value!=None:
        sGx.cell(row=u, column=9).value=sGx.cell(row=u, column=8).value/sGx.cell(row=u,
column=2).value
    else:
        sGx.cell(row=u, column=9).value="--"
    if sGx.cell(row=u, column=14).value!=None and sGx.cell(row=u, column=15).value!=None:
        sGx.cell(row=u, column=16).value=sGx.cell(row=u, column=14).value+sGx.cell(row=u,
column=15).value
    else:
        sGx.cell(row=u, column=16).value="--"
    if sSx.cell(row=u, column=7).value!=0 and sGx.cell(row=u, column=7).value!=None and
sGx.cell(row=u, column=7).value!="--" and sGx.cell(row=u, column=9).value!=0 and sGx.cell(row=u,
column=9).value!=None and sSx.cell(row=u, column=9).value!="--":
        sGx.cell(row=u, column=18).value=sGx.cell(row=u, column=9).value/sGx.cell(row=u,
column=7).value
    else:
        sGx.cell(row=u, column=18).value="--"
    if sGx.cell(row=u, column=8).value!=0 and sGx.cell(row=u, column=8).value!=None and
sGx.cell(row=u, column=6).value!=0 and sGx.cell(row=u, column=6).value!=None and sGx.cell(row=u,
column=6).value!="--" and sSx.cell(row=u, column=8).value!="--":
        sGx.cell(row=u, column=17).value=sGx.cell(row=u, column=8).value/sGx.cell(row=u,
column=6).value
    else:
        sGx.cell(row=u, column=17).value="--"

#####
for i in range (1, s1.max_column, 3):
    n=s1.cell(row=2, column=i).value

```

```

if p[n]==[]:
    print(n+ " no phases")
else:
    for u in range (4, blankrow(i, s1, 4)):
        x=p[n]
        if s1.cell(row=u, column=i).value< x[0] or s1.cell(row=u, column=i).value> x[len(x)-
1]:

            #len(x)-1 because its starts counting at 0
            s1.cell(row=u, column=i+1).value=0
        else:
            for o in range (1, len(x),2):
                if x[o]<s1.cell(row=u, column=i).value<x[o+1]:
                    s1.cell(row=u, column=i+1).value=0

#iTRIMP (before change to %maxHR)
soutput.merge_cells(start_row=1, start_column=8, end_row=1, end_column=10)
soutput.cell(row=1, column=8).value='iTRIMP'
soutput.cell(row=2, column=8).value='1st Half'
soutput.cell(row=2, column=9).value='2nd Half'
soutput.cell(row=2, column=10).value="Game"
y2=3
for i in range (2, s1.max_column+1, 3):
    x21=0
    x22=0
    x23=0
    Max=MaxHR[s1.cell(row=2, column=i-1).value]
    Min=MinHR[s1.cell(row=2, column=i-1).value]
    a=aValue[s1.cell(row=2, column=i-1).value]
    b=bValue[s1.cell(row=2, column=i-1).value]
    if a!="--":
        for u in range (4, blankrow(i,s1,4)):
            HRR=(s1.cell(row=u, column=i).value-Min)/(Max-Min)
            if 1.02>HRR>0:
                if type(halftime)!=datetime.time:
                    x23+=HRR*a*math.exp(b*HRR)
                else:
                    if s1.cell(row=u, column=i-1).value<halftime:
                        x21+=HRR*a*math.exp(b*HRR)
                    elif s1.cell(row=u, column=i-1).value>=halftime:
                        x22+=HRR*a*math.exp(b*HRR)
                    x23=x21+x22
            soutput.cell(row=y2, column=10).value=x23/60
            soutput.cell(row=y2, column=8).value=x21/60
            soutput.cell(row=y2, column=9).value=x22/60
        else:
            soutput.cell(row=y2, column=10).value="--"
            soutput.cell(row=y2, column=8).value="--"
            soutput.cell(row=y2, column=9).value="--"
    y2+=1

#Changes to %max HR
for i in range (2, s1.max_column+1, 3):
    HR=MaxHR[s1.cell(row=2, column=i-1).value]
    for u in range (4, blankrow(i,s1,4)):
        s1.cell(row=u, column=i).value= s1.cell(row=u, column=i).value/HR

#Stagno TRIMP
soutput.merge_cells(start_row=1, start_column=2, end_row=1, end_column=4)

```

```
soutput.cell(row=1, column=2).value='sTRIMP'
soutput.cell(row=2, column=2).value='1st Half'
soutput.cell(row=2, column=3).value='2nd Half'
soutput.cell(row=2, column=4).value="Game"
```

```
y1=3
for i in range (2, s1.max_column+1, 3):
    x11=0
    x12=0
    x13=0
    for u in range (4, blankrow(i, s1, 4)):
        if type(halftime)!=datetime.time:
            if 0.715>s1.cell(row=u, column=i).value>=0.645:
                x13+=1.25
            elif 0.785>s1.cell(row=u, column=i).value>=0.715:
                x13+=1.71
            elif .855>s1.cell(row=u, column=i).value>=0.785:
                x13+=2.54
            elif .925>s1.cell(row=u, column=i).value>=.855:
                x13+=3.61
            elif 1.02>s1.cell(row=u, column=i).value>=.925:
                x13+=5.16
        else:
            if s1.cell(row=u, column=i-1).value<halftime:
                if 0.715>s1.cell(row=u, column=i).value>=0.645:
                    x11+=1.25
                elif 0.785>s1.cell(row=u, column=i).value>=0.715:
                    x11+=1.71
                elif .855>s1.cell(row=u, column=i).value>=0.785:
                    x11+=2.54
                elif .925>s1.cell(row=u, column=i).value>=.855:
                    x11+=3.61
                elif 1.02>s1.cell(row=u, column=i).value>=.925:
                    x11+=5.16
            elif s1.cell(row=u, column=i-1).value>=halftime:
                if 0.715>s1.cell(row=u, column=i).value>=0.645:
                    x12+=1.25
                elif 0.785>s1.cell(row=u, column=i).value>=0.715:
                    x12+=1.71
                elif .855>s1.cell(row=u, column=i).value>=0.785:
                    x12+=2.54
                elif .925>s1.cell(row=u, column=i).value>=.855:
                    x12+=3.61
                elif 1.02>s1.cell(row=u, column=i).value>=.925:
                    x12+=5.16
            x13=x11+x12
    soutput.cell(row=y1, column=1).value= s1.cell(row=2, column=i-1).value
    soutput.cell(row=y1, column=4).value=x13/60
    soutput.cell(row=y1, column=3).value=x12/60
    soutput.cell(row=y1, column=2).value=x11/60
    soutput.cell(row=y1, column=2).value=x11/60
    y1+=1
```

#FTRIMP

```
soutput.merge_cells(start_row=1, start_column=5, end_row=1, end_column=7)
soutput.cell(row=1, column=5).value='nTRIMP'
soutput.cell(row=2, column=5).value='1st Half'
soutput.cell(row=2, column=6).value='2nd Half'
soutput.cell(row=2, column=7).value="Game"
```

```

y3=3
for i in range (2, s1.max_column+1, 3):
    x31=0
    x32=0
    x33=0
    for u in range (4, blankrow(i, s1, 4)):
        if type(halftime)!=datetime.time:
            if 0.67>s1.cell(row=u, column=i).value>=0.59:
                x33+=0.91
            elif 0.75>s1.cell(row=u, column=i).value>=0.67:
                x33+=1.49
            elif .83>s1.cell(row=u, column=i).value>=0.75:
                x33+=2.44
            elif .91>s1.cell(row=u, column=i).value>=0.83:
                x33+=3.99
            elif 1.02>s1.cell(row=u, column=i).value>=0.91:
                x33+=6.74
        else:
            if s1.cell(row=u, column=i-1).value<halftime:
                if 0.67>s1.cell(row=u, column=i).value>=0.59:
                    x31+=0.91
                elif 0.75>s1.cell(row=u, column=i).value>=0.67:
                    x31+=1.49
                elif .83>s1.cell(row=u, column=i).value>=0.75:
                    x31+=2.44
                elif .91>s1.cell(row=u, column=i).value>=0.83:
                    x31+=3.99
                elif 1.02>s1.cell(row=u, column=i).value>=0.91:
                    x31+=6.74
            elif s1.cell(row=u, column=i-1).value>=halftime:
                if 0.67>s1.cell(row=u, column=i).value>=0.59:
                    x32+=0.91
                elif 0.75>s1.cell(row=u, column=i).value>=0.67:
                    x32+=1.49
                elif .83>s1.cell(row=u, column=i).value>=0.75:
                    x32+=2.44
                elif .91>s1.cell(row=u, column=i).value>=0.83:
                    x32+=3.99
                elif 1.02>s1.cell(row=u, column=i).value>=0.91:
                    x32+=6.74
            x33=x31+x32
    soutput.cell(row=y3, column=5).value=x31/60
    soutput.cell(row=y3, column=6).value=x32/60
    soutput.cell(row=y3, column=7).value=x33/60
    y3+=1

wboutput.create_sheet('1st Half')
s1sthalf=wboutput['1st Half']
wboutput.create_sheet('2nd Half')
s2ndhalf=wboutput['2nd Half']
wboutput.create_sheet('Game')
sgame=wboutput['Game']

headings=["Name", "Minutes", "Position", "sTRIMP", "nTRIMP", "iTRIMP", "% Max HR", "TD", "Workrate",
"Zone 1", "Zone 2", "Zone 3", "Zone 4", "Zone 5", "Zone 6", "Zone 7", "Effindex 1", "Effindex 2"]
for u in range(0,18):
    s1sthalf.cell(row=1, column=u+1).value=headings[u]
    s2ndhalf.cell(row=1, column=u+1).value=headings[u]

```

```

headings2=["Name", "Minutes", "Position", "rRPE", "uRPE", "lRPE", "oRPE", "sTRIMP", "nTRIMP",
"iTRIMP", "% Max HR", "TD", "Workrate", "Zone 1", "Zone 2", "Zone 3", "Zone 4", "Zone 5", "Zone 6",
"Zone 7", "Effindex 1", "Effindex 2"]

```

```

for u in range(0,22):

```

```

    sgame.cell(row=1, column=u+1).value=headings2[u]

```

```

for u in range(3, blankrow(1,soutput, 3)):

```

```

    s1sthalf.cell(row=u-1, column=1).value=soutput.cell(row=u, column=1).value
    s1sthalf.cell(row=u-1, column=4).value=soutput.cell(row=u, column=2).value
    s1sthalf.cell(row=u-1, column=5).value=soutput.cell(row=u, column=5).value
    s1sthalf.cell(row=u-1, column=6).value=soutput.cell(row=u, column=8).value
    s2ndhalf.cell(row=u-1, column=1).value=soutput.cell(row=u, column=1).value
    s2ndhalf.cell(row=u-1, column=4).value=soutput.cell(row=u, column=3).value
    s2ndhalf.cell(row=u-1, column=5).value=soutput.cell(row=u, column=6).value
    s2ndhalf.cell(row=u-1, column=6).value=soutput.cell(row=u, column=9).value
    sgame.cell(row=u-1, column=1).value=soutput.cell(row=u, column=1).value
    sgame.cell(row=u-1, column=8).value=soutput.cell(row=u, column=4).value
    sgame.cell(row=u-1, column=9).value=soutput.cell(row=u, column=7).value
    sgame.cell(row=u-1, column=10).value=soutput.cell(row=u, column=10).value

```

```

TD1={}

```

```

TD2={}

```

```

M1={}

```

```

M2={}

```

```

Z11={}

```

```

Z12={}

```

```

Z21={}

```

```

Z22={}

```

```

Z31={}

```

```

Z32={}

```

```

Z41={}

```

```

Z42={}

```

```

Z51={}

```

```

Z52={}

```

```

Z61={}

```

```

Z62={}

```

```

for u in range (2, blankrow(1,s1sthalf,2)):

```

```

    TD1[s1sthalf.cell(row=u, column=1).value]=TD2[s1sthalf.cell(row=u,
column=1).value]=M1[s1sthalf.cell(row=u, column=1).value]=M2[s1sthalf.cell(row=u,
column=1).value]=Z11[s1sthalf.cell(row=u, column=1).value]=Z12[s1sthalf.cell(row=u,
column=1).value]=Z21[s1sthalf.cell(row=u, column=1).value]=Z22[s1sthalf.cell(row=u,
column=1).value]=Z31[s1sthalf.cell(row=u, column=1).value]=Z32[s1sthalf.cell(row=u,
column=1).value]=Z41[s1sthalf.cell(row=u, column=1).value]=Z42[s1sthalf.cell(row=u,
column=1).value]=Z51[s1sthalf.cell(row=u, column=1).value]=Z52[s1sthalf.cell(row=u,
column=1).value]=Z61[s1sthalf.cell(row=u, column=1).value]=Z62[s1sthalf.cell(row=u, column=1).value]=0

```

```

    for i in range (2, blankrow(1, speriods,2)):

```

```

        if s1sthalf.cell(row=u, column=1).value==speriods.cell(row=i, column=1).value:

```

```

            if speriods.cell(row=i, column=2).value!="Session":

```

```

                if speriods.cell(row=i, column=2).value[-1]==kValue[speriods.cell(row=i,

```

```

column=1).value]:

```

```

                    if speriods.cell(row=i, column=2).value[0]=="1":

```

```

                        TD1[s1sthalf.cell(row=u,

```

```

column=1).value]+=speriods.cell(row=i, column=10).value

```

```

                        M1[s1sthalf.cell(row=u,

```

```

column=1).value]+=minutes(datetime.datetime.strptime("0"+speriods.cell(row=i, column=8).value,

```

```

"%H:%M:%S").time())

```

```

                        Z11[s1sthalf.cell(row=u,

```

```

column=1).value]+=speriods.cell(row=i, column=12).value

```

```

        Z21[s1sthalf.cell(row=u,
column=1).value]+=speriods.cell(row=i, column=13).value
        Z31[s1sthalf.cell(row=u,
column=1).value]+=speriods.cell(row=i, column=14).value
        Z41[s1sthalf.cell(row=u,
column=1).value]+=speriods.cell(row=i, column=15).value
        Z51[s1sthalf.cell(row=u,
column=1).value]+=speriods.cell(row=i, column=16).value
        Z61[s1sthalf.cell(row=u,
column=1).value]+=speriods.cell(row=i, column=17).value
        if speriods.cell(row=i, column=2).value[0]=="2":
            TD2[s1sthalf.cell(row=u,
column=1).value]+=speriods.cell(row=i, column=10).value
            M2[s1sthalf.cell(row=u,
column=1).value]+=minutes(datetime.datetime.strptime("0"+speriods.cell(row=i, column=8).value,
"%H:%M:%S").time())
            Z12[s1sthalf.cell(row=u,
column=1).value]+=speriods.cell(row=i, column=12).value
            Z22[s1sthalf.cell(row=u,
column=1).value]+=speriods.cell(row=i, column=13).value
            Z32[s1sthalf.cell(row=u,
column=1).value]+=speriods.cell(row=i, column=14).value
            Z42[s1sthalf.cell(row=u,
column=1).value]+=speriods.cell(row=i, column=15).value
            Z52[s1sthalf.cell(row=u,
column=1).value]+=speriods.cell(row=i, column=16).value
            Z62[s1sthalf.cell(row=u,
column=1).value]+=speriods.cell(row=i, column=17).value
            s1sthalf.cell(row=u, column=2).value=M1[s1sthalf.cell(row=u, column=1).value]
            s1sthalf.cell(row=u, column=8).value=TD1[s1sthalf.cell(row=u, column=1).value]
            s1sthalf.cell(row=u, column=10).value=Z11[s1sthalf.cell(row=u, column=1).value]
            s1sthalf.cell(row=u, column=11).value=Z21[s1sthalf.cell(row=u, column=1).value]
            s1sthalf.cell(row=u, column=12).value=Z31[s1sthalf.cell(row=u, column=1).value]
            s1sthalf.cell(row=u, column=13).value=Z41[s1sthalf.cell(row=u, column=1).value]
            s1sthalf.cell(row=u, column=14).value=Z51[s1sthalf.cell(row=u, column=1).value]
            s1sthalf.cell(row=u, column=15).value=Z61[s1sthalf.cell(row=u, column=1).value]
            s2ndhalf.cell(row=u, column=2).value=M2[s1sthalf.cell(row=u, column=1).value]
            s2ndhalf.cell(row=u, column=8).value=TD2[s1sthalf.cell(row=u, column=1).value]
            s2ndhalf.cell(row=u, column=10).value=Z12[s1sthalf.cell(row=u, column=1).value]
            s2ndhalf.cell(row=u, column=11).value=Z22[s1sthalf.cell(row=u, column=1).value]
            s2ndhalf.cell(row=u, column=12).value=Z32[s1sthalf.cell(row=u, column=1).value]
            s2ndhalf.cell(row=u, column=13).value=Z42[s1sthalf.cell(row=u, column=1).value]
            s2ndhalf.cell(row=u, column=14).value=Z52[s1sthalf.cell(row=u, column=1).value]
            s2ndhalf.cell(row=u, column=15).value=Z62[s1sthalf.cell(row=u, column=1).value]
            sgame.cell(row=u, column=2).value=M1[s1sthalf.cell(row=u,
column=1).value]+M2[s1sthalf.cell(row=u, column=1).value]
            sgame.cell(row=u, column=12).value=TD1[s1sthalf.cell(row=u,
column=1).value]+TD2[s1sthalf.cell(row=u, column=1).value]
            sgame.cell(row=u, column=14).value=Z11[s1sthalf.cell(row=u,
column=1).value]+Z12[s1sthalf.cell(row=u, column=1).value]
            sgame.cell(row=u, column=15).value=Z21[s1sthalf.cell(row=u,
column=1).value]+Z22[s1sthalf.cell(row=u, column=1).value]
            sgame.cell(row=u, column=16).value=Z31[s1sthalf.cell(row=u,
column=1).value]+Z32[s1sthalf.cell(row=u, column=1).value]
            sgame.cell(row=u, column=17).value=Z41[s1sthalf.cell(row=u,
column=1).value]+Z42[s1sthalf.cell(row=u, column=1).value]
            sgame.cell(row=u, column=18).value=Z51[s1sthalf.cell(row=u,
column=1).value]+Z52[s1sthalf.cell(row=u, column=1).value]
            sgame.cell(row=u, column=19).value=Z61[s1sthalf.cell(row=u,
column=1).value]+Z62[s1sthalf.cell(row=u, column=1).value]

```

```

        if M1[s1sthalf.cell(row=u, column=1).value]!=0:
            s1sthalf.cell(row=u, column=9).value=TD1[s1sthalf.cell(row=u,
column=1).value]/M1[s1sthalf.cell(row=u, column=1).value]
        else:
            s1sthalf.cell(row=u, column=9).value="--"
        if M2[s1sthalf.cell(row=u, column=1).value]!=0:
            s2ndhalf.cell(row=u, column=9).value=TD2[s2ndhalf.cell(row=u,
column=1).value]/M2[s2ndhalf.cell(row=u, column=1).value]
        else:
            s2ndhalf.cell(row=u, column=9).value="--"
        if sgame.cell(row=u, column=2).value!=0:
            sgame.cell(row=u, column=13).value=sgame.cell(row=u,
column=12).value/sgame.cell(row=u, column=2).value
        else:
            sgame.cell(row=u, column=13).value="--"

```

```

y4=2
for i in range (2, s1.max_column+1, 3):
    m=m1=m2=c=c1=c2=0
    for u in range (4, blankrow(i, s1, 4)):
        if s1.cell(row=u, column=i).value!=0:
            m+=s1.cell(row=u, column=i).value
            c+=1
            if s1.cell(row=u, column=i-1).value<halftime:
                m1+=s1.cell(row=u, column=i).value
                c1+=1
            elif s1.cell(row=u, column=i-1).value>=halftime:
                m2+=s1.cell(row=u, column=i).value
                c2+=1
        if c==0:
            sgame.cell(row=y4, column=11).value="--"
        else:
            sgame.cell(row=y4, column=11).value=m/c
        if c1==0:
            s1sthalf.cell(row=y4, column=7).value="--"
        else:
            s1sthalf.cell(row=y4, column=7).value=m1/c1
        if c2==0:
            s2ndhalf.cell(row=y4, column=7).value="--"
        else:
            s2ndhalf.cell(row=y4, column=7).value=m2/c2
        y4+=1

```

```

for u in range(1, blankrow(2, sRPEs, 1)):
    for i in range (1, blankrow(1, sgame, 2)):
        if sRPEs.cell(row=u, column=1).value==sgame.cell(row=i, column=1).value:
            if sgame.cell(row=i, column=2).value==None or sgame.cell(row=i,
column=2).value==0:
                sgame.cell(row=i, column=7).value=sgame.cell(row=i,
column=4).value = sgame.cell(row=i, column=5).value= sgame.cell(row=i, column=6).value="--"
            else:
                sgame.cell(row=i, column=4).value=sRPEs.cell(row=u,
column=2).value * sgame.cell(row=i, column=2).value/10
                sgame.cell(row=i, column=5).value=sRPEs.cell(row=u,
column=3).value * sgame.cell(row=i, column=2).value/10
                sgame.cell(row=i, column=6).value=sRPEs.cell(row=u,
column=4).value * sgame.cell(row=i, column=2).value/10
                sgame.cell(row=i, column=7).value=sRPEs.cell(row=u,
column=5).value * sgame.cell(row=i, column=2).value/10

```

```

for u in range(2, blankrow(1, sgame, 2)):
    if sgame.cell(row=u, column=18).value==None or sgame.cell(row=u, column=19).value==None:
        sgame.cell(row=u, column=20).value="--"
    else:
        sgame.cell(row=u, column=20).value=sgame.cell(row=u,
column=18).value+sgame.cell(row=u, column=19).value
        if sgame.cell(row=u, column=12).value==None or sgame.cell(row=u, column=10).value==None or
sgame.cell(row=u, column=10).value==0 or sgame.cell(row=u, column=10).value=="--":
            sgame.cell(row=u, column=21).value="--"
        else:
            sgame.cell(row=u, column=21).value=sgame.cell(row=u,
column=12).value/sgame.cell(row=u, column=10).value
            if sgame.cell(row=u, column=13).value==None or sgame.cell(row=u, column=11).value==None or
sgame.cell(row=u, column=11).value==0 or sgame.cell(row=u, column=13).value=="--" or sgame.cell(row=u,
column=11).value=="--":
                sgame.cell(row=u, column=22).value="--"
            else:
                sgame.cell(row=u, column=22).value=sgame.cell(row=u,
column=13).value/sgame.cell(row=u, column=11).value

halves=[s1sthalf,s2ndhalf]
for i in range(0,2):
    for u in range(2, blankrow(1, halves[i], 2)):
        if halves[i].cell(row=u, column=14).value==None or halves[i].cell(row=u,
column=15).value==None:
            halves[i].cell(row=u, column=16).value="--"
        else:
            halves[i].cell(row=u, column=16).value=halves[i].cell(row=u,
column=14).value+halves[i].cell(row=u, column=15).value
            if halves[i].cell(row=u, column=8).value==None or halves[i].cell(row=u,
column=6).value==None or halves[i].cell(row=u, column=6).value==0 or halves[i].cell(row=u,
column=6).value=="--":
                halves[i].cell(row=u, column=17).value="--"
            else:
                halves[i].cell(row=u, column=17).value=halves[i].cell(row=u,
column=8).value/halves[i].cell(row=u, column=6).value
                if halves[i].cell(row=u, column=7).value==None or halves[i].cell(row=u,
column=9).value==None or halves[i].cell(row=u, column=7).value==0 or halves[i].cell(row=u,
column=9).value=="--" or halves[i].cell(row=u, column=7).value=="--":
                    halves[i].cell(row=u, column=18).value="--"
                else:
                    halves[i].cell(row=u, column=18).value=halves[i].cell(row=u,
column=9).value/halves[i].cell(row=u, column=7).value

wboutput.save(output)

```



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